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# On-line Reinforcement Learning Using Incremental Kernel-Based Stochastic Factorization

## SUPPLEMENTARY MATERIAL

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### Abstract

This is the supplementary material for the paper entitled “On-line Reinforcement Learning Using Incremental Kernel-Based Stochastic Factorization” [2]. It contains the details of our theoretical developments that could not be included in the paper due to space constraints. This material should be read in conjunction with the main paper.

## 1 Preliminaries

- Similarly to Ormoneit and Sen [3], we define a “mother kernel”  $\phi(x) : \mathbb{R}^+ \mapsto \mathbb{R}^+$  satisfying
  - (i)  $\phi(x)$  is continuous in  $\mathbb{R}^+$ ,
  - (ii)  $\int_0^\infty \phi(x) dx \leq L_\phi < \infty$ ,
  - (iii)  $\phi(x) \geq \phi(y)$  if  $x < y$ ,
  - (iv)  $\exists A_\phi, \lambda_\phi > 0, \exists B_\phi \geq 0$  such that  $A_\phi \exp(-x) \leq \phi(x) \leq \lambda_\phi A_\phi \exp(-x)$  if  $x \geq B_\phi$ .

### Remarks:

- Assumption (i) is implied by Ormoneit and Sen’s [3] assumption that  $\phi$  is Lipschitz continuous. Ormoneit and Sen also assume that  $\int_0^1 \phi(z) dz = 1$  (see Appendix A.1 in [3]).
- Assumption (iv) implies that the kernel function  $\phi$  will eventually decay exponentially and also that  $\phi(z) > 0$  for all  $z \in \mathbb{R}^+$ .
- Let  $\mathbb{S} \subset [0, 1]^d$  and let  $\|\cdot\|$  be a norm in  $\mathbb{R}^d$ . Then, we define

$$k_\tau(s, s') = \phi\left(\frac{\|s - s'\|}{\tau}\right),$$

where  $\tau > 0$  is the “width” of the kernel  $k_\tau$ .

- Let  $M$  be a Markov decision process (MDP) with state space  $\mathbb{S}$  and let  $S^a = \{(s_k^a, r_k^a, \hat{s}_k^a) \mid k = 1, 2, \dots, n_a\}$  be a set of sample transitions associated with action  $a \in A$ , where  $s_k^a, \hat{s}_k^a \in \mathbb{S}$  and  $r_k^a \in \mathbb{R}$ . We define the normalized kernel function associated with action  $a$  as

$$\kappa_\tau^a(s, s_i^a) = \frac{k_\tau(s, s_i^a)}{\sum_{j=1}^{n_a} k_\tau(s, s_j^a)}.$$

- Let  $\bar{S} \equiv \{\bar{s}_1, \bar{s}_2, \dots, \bar{s}_m\}$  be a set of representative states in  $\mathbb{S}$ . Define:
  - $\hat{s}_*^a \equiv \hat{s}_k^a$  with  $k = \operatorname{argmax}_i \min_j \|\hat{s}_i^a - \bar{s}_j\|$ ,

- $\bar{s}_*^a \equiv \bar{s}_h$  where  $h = \operatorname{argmin}_j \| \hat{s}_*^a - \bar{s}_j \|$ ,
- $\hat{s}_* \equiv \hat{s}_*^b$  where  $b = \operatorname{argmax}_a \| \hat{s}_*^a - \bar{s}_*^a \|$ ,
- $\bar{s}_* \equiv \bar{s}_*^b$  where  $b = \operatorname{argmax}_a \| \hat{s}_*^a - \bar{s}_*^a \|$ ,
- $\vartheta^* \equiv \| \hat{s}_* - \bar{s}_* \|$ .

We assume that

- (v)  $\hat{s}_*^a$  and  $\bar{s}_*^a$  are unique for all  $a \in A$ .

## 2 Data-independent definitions

**Definition 1.** For any  $\alpha \in (0, 1]$ , the  $\alpha$ -radius of  $k_\tau$  with respect to  $s$  and  $s'$  is defined as

$$\rho(k_\tau, s, s', \alpha) = \max \left\{ x \in \mathbb{R}^+ \mid \phi \left( \frac{x}{\tau} \right) = \alpha k_\tau(s, s') \right\}.$$

**Remarks:**

- The existence of  $\rho(k_\tau, s, s', \alpha)$  is guaranteed by properties (i), (ii) and (iii).
- $\rho(k_\tau, s, s', \alpha) \geq \| s - s' \|$ .

**Property 1.** If  $\| s - s' \| < \| s - s'' \|$ , then  $\rho(k_\tau, s, s', \alpha) \leq \rho(k_\tau, s, s'', \alpha)$ .

*Proof.* Let  $r = \rho(k_\tau, s, s', \alpha)$ . Then,

$$\phi \left( \frac{r}{\tau} \right) = \alpha k_\tau(s, s') = \alpha \phi \left( \frac{\| s - s' \|}{\tau} \right) \geq \alpha \phi \left( \frac{\| s - s'' \|}{\tau} \right) = \alpha k_\tau(s, s'').$$

If  $\phi(r/\tau) = \alpha k_\tau(s, s'')$ , then  $\rho(k_\tau, s, s'', \alpha) = r$ . If  $\phi(r/\tau) > \alpha k_\tau(s, s'')$ , then from (iii) it must be the case that  $r < \rho(k_\tau, s, s'', \alpha)$ .  $\square$

**Property 2.** If  $\alpha < \alpha'$ , then  $\rho(k_\tau, s, s', \alpha) > \rho(k_\tau, s, s', \alpha')$ .

*Proof.* Let  $r = \rho(k_\tau, s, s', \alpha')$ . Then,

$$\phi \left( \frac{r}{\tau} \right) = \alpha' k_\tau(s, s') = \alpha' \phi \left( \frac{\| s - s' \|}{\tau} \right) > \alpha \phi \left( \frac{\| s - s' \|}{\tau} \right) = \alpha k_\tau(s, s').$$

From (iii) it must be the case that  $r < \rho(k_\tau, s, s', \alpha)$ .  $\square$

**Property 3.** For any  $\alpha \in (0, 1)$  and any  $\varepsilon > 0$ , there is a  $\delta > 0$  such that  $\rho(k_\tau, s, s', \alpha) - \| s - s' \| < \varepsilon$  if  $\tau < \delta$ .

*Proof.* Let  $z = \| s - s' \|$ . We will show that, for any  $\varepsilon > 0$ , there is a  $\delta > 0$  such that  $\phi((z + \varepsilon)/\tau) < \alpha \phi(z/\tau)$  if  $\tau < \delta$ . We know that

$$\begin{aligned} \frac{\exp(-(z + \varepsilon)/\tau)}{\exp(-z/\tau)} < \alpha/\lambda_\phi &\iff \ln \left( \frac{\exp(-(z + \varepsilon)/\tau)}{\exp(-z/\tau)} \right) < \ln(\alpha/\lambda_\phi) \iff \\ &\iff -\frac{\varepsilon}{\tau} < \ln(\alpha/\lambda_\phi) \iff \tau < -\frac{\varepsilon}{\ln(\alpha/\lambda_\phi)} \end{aligned}$$

(note that it must be the case that  $\alpha/\lambda_\phi \neq 1$ ). Thus, by taking  $\delta < \min(-\varepsilon/\ln(\alpha/\lambda_\phi), z/B_\phi)$  and resorting to Assumption (iv), we can write:

$$\begin{aligned} \alpha/\lambda_\phi &> \frac{\exp(-(z + \varepsilon)/\delta)}{\exp(-z/\delta)} = \frac{A_\phi \exp(-(z + \varepsilon)/\delta)}{A_\phi \exp(-z/\delta)} \\ &\geq \frac{A_\phi \exp(-(z + \varepsilon)/\delta)}{\lambda_\phi A_\phi \exp(-(z + \varepsilon)/\delta)} = \frac{\phi(z/\delta)}{\lambda_\phi \phi(z/\delta)} \\ &\geq \frac{\phi((z + \varepsilon)/\delta)}{\lambda_\phi \phi(z/\delta)}, \end{aligned}$$

and therefore  $\frac{\phi((z + \varepsilon)/\tau)}{\phi(z/\tau)} < \alpha$  if  $\tau \leq \delta$ .  $\square$

**Remarks:**

- $\rho(k_\tau, s, s', \alpha) - \|s - s'\| < \varepsilon$  if  $\tau < \min(-\varepsilon / \ln(\alpha / \lambda_\phi), \|s - s'\| / B_\phi)$ , where  $\lambda_\phi$  and  $B_\phi$  depend on the particular choice of function  $\phi$  (see Assumption (iv)).
- Given  $s, s'$ , and  $s''$ , with  $\|s - s'\| < \|s - s''\|$ , Property 3 states that for any  $\alpha \in (0, 1)$ , there is a  $\delta > 0$  such that  $k_\tau(s, s'') < \alpha k_\tau(s, s')$  if  $\tau < \delta$  (to see why this is so, it suffices to make  $\varepsilon = \|s - s''\| - \|s - s'\|$ ).

### 3 Data-dependent definitions

**Definition 2.** Given  $\beta > 0$ , the  $\beta$ -dissimilarity between  $s$  and  $s'$  with respect to  $\kappa_\tau^\alpha$  is defined as

$$\psi(\kappa_\tau^\alpha, s, s', \beta) = \begin{cases} \sum_{k=1}^{n_a} |\kappa_\tau^\alpha(s, s_k^\alpha) - \kappa_\tau^\alpha(s', s_k^\alpha)|, & \text{if } \|s - s'\| \leq \beta, \\ 0, & \text{otherwise.} \end{cases}$$

**Remark:**  $\psi(\kappa_\tau^\alpha, s, s', \beta) \in [0, 2]$ .

**Property 4.** For any  $\beta > 0$  and any  $\varepsilon > 0$ , there is a  $\delta > 0$  such that  $\psi(\kappa_\tau^\alpha, s, s', \beta) < \varepsilon$  if  $\|s - s'\| < \delta$ .

*Proof.* If  $\beta < \|s - s'\|$ , then  $\psi(\kappa_\tau^\alpha, s, s', \beta) = 0$  and the result follows (see Definition 2). Otherwise:

$$\begin{aligned} \psi(\kappa_\tau^\alpha, s, s', \beta) &\equiv \psi_{\tau, s, \beta}^\alpha(s') = \sum_{k=1}^{n_a} \left| \frac{k_\tau(s, s_k^\alpha)}{\sum_{l=1}^{n_a} k_\tau(s, s_l^\alpha)} - \frac{k_\tau(s', s_k^\alpha)}{\sum_{l=1}^{n_a} k_\tau(s', s_l^\alpha)} \right| \\ &= \sum_{k=1}^{n_a} \left| \frac{\phi(\|s - s_k^\alpha\|/\tau)}{\sum_{l=1}^{n_a} \phi(\|s - s_l^\alpha\|/\tau)} - \frac{\phi(\|s' - s_k^\alpha\|/\tau)}{\sum_{l=1}^{n_a} \phi(\|s' - s_l^\alpha\|/\tau)} \right|. \end{aligned}$$

From the definition of  $\phi$ , it is obvious that  $\psi_{\tau, s, \beta}^\alpha(s')$  is continuous in  $s'$ . The property follows from the fact that  $\lim_{s' \rightarrow s} \psi_{\tau, s, \beta}^\alpha(s') = 0$ .  $\square$

**Remarks:**

- $\psi(\kappa_\tau^\alpha, s, s', \beta)$  does not necessarily increase with  $\|s - s'\|$ .
- Given  $\varepsilon > 0$ ,  $\delta$  is data-dependent.

### 4 Main Results

**Lemma 1.** For any  $\alpha \in (0, 1]$  and any  $t \geq m - 1$ , let  $\delta_a = \rho(k_{\bar{\tau}}, \bar{s}_*^\alpha, \bar{s}_*^\alpha, \alpha/t)$ , let  $\psi_\delta^\alpha = \max_{i,j} \psi(\kappa_\tau^\alpha, \bar{s}_i^\alpha, \bar{s}_j, \delta_a)$  and let  $\psi_{\max}^\alpha = \max_{i,j} \psi(\kappa_\tau^\alpha, \bar{s}_i^\alpha, \bar{s}_j, \infty)$ . Then,

$$\|\mathbf{P}^a - \mathbf{DK}^a\|_\infty \leq \frac{1}{1 + \alpha} \psi_\delta^\alpha + \frac{\alpha}{1 + \alpha} \psi_{\max}^\alpha. \quad (1)$$

*Proof.* Let  $\tilde{\mathbf{P}}^a = \mathbf{D}\mathbf{K}^a$ . Recalling that  $\kappa_\tau^a(s, s_j^a) = \frac{\mathbf{k}_\tau(s, s_j^a)}{\sum_{k=1}^{n_a} \mathbf{k}_\tau(s, s_k^a)}$ , we can write:

$$\begin{aligned}
\|\mathbf{p}_i^a - \tilde{\mathbf{p}}_i^a\|_1 &= \sum_{j=1}^{n_a} |p_{ij}^a - \sum_{k=1}^m d_{ik}^a k_{kj}^a| \\
&= \sum_{j=1}^{n_a} \left| \frac{\mathbf{k}_\tau(\hat{s}_i^a, s_j^a)}{\sum_{l=1}^n \mathbf{k}_\tau(\hat{s}_i^a, s_l^a)} - \sum_{k=1}^m \left( \frac{\mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \frac{\mathbf{k}_\tau(\bar{s}_k, s_j^a)}{\sum_{l=1}^n \mathbf{k}_\tau(\bar{s}_k, s_l^a)} \right) \right| \\
&= \sum_{j=1}^{n_a} \left| \frac{\mathbf{k}_\tau(\hat{s}_i^a, s_j^a)}{\sum_{l=1}^n \mathbf{k}_\tau(\hat{s}_i^a, s_l^a)} - \frac{1}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \sum_{k=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k) \frac{\mathbf{k}_\tau(\bar{s}_k, s_j^a)}{\sum_{l=1}^n \mathbf{k}_\tau(\bar{s}_k, s_l^a)} \right| \\
&= \sum_{j=1}^{n_a} \left| \frac{1}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \sum_{k=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k) \frac{\mathbf{k}_\tau(\hat{s}_i^a, s_j^a)}{\sum_{l=1}^n \mathbf{k}_\tau(\hat{s}_i^a, s_l^a)} - \frac{1}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \sum_{k=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k) \frac{\mathbf{k}_\tau(\bar{s}_k, s_j^a)}{\sum_{l=1}^n \mathbf{k}_\tau(\bar{s}_k, s_l^a)} \right| \\
&\leq \sum_{j=1}^{n_a} \frac{1}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \sum_{k=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k) \left| \frac{\mathbf{k}_\tau(\hat{s}_i^a, s_j^a)}{\sum_{l=1}^n \mathbf{k}_\tau(\hat{s}_i^a, s_l^a)} - \frac{\mathbf{k}_\tau(\bar{s}_k, s_j^a)}{\sum_{l=1}^n \mathbf{k}_\tau(\bar{s}_k, s_l^a)} \right| \\
&= \frac{1}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \sum_{k=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k) \sum_{j=1}^{n_a} |\kappa_\tau^a(\hat{s}_i^a, s_j^a) - \kappa_\tau^a(\bar{s}_k, s_j^a)|.
\end{aligned}$$

Let  $H = \{k \mid \|\hat{s}_i^a - \bar{s}_k\| \leq \delta_a\}$  and let  $\bar{H} = \{1, 2, \dots, m\} - H$ . Then,

$$\begin{aligned}
\|\mathbf{p}_i^a - \tilde{\mathbf{p}}_i^a\|_1 &\leq \sum_{k \in H} \frac{\mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \sum_{j=1}^{n_a} |\kappa_\tau^a(\hat{s}_i^a, s_j^a) - \kappa_\tau^a(\bar{s}_k, s_j^a)| + \sum_{k \in \bar{H}} \frac{\mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \sum_{j=1}^{n_a} |\kappa_\tau^a(\hat{s}_i^a, s_j^a) - \kappa_\tau^a(\bar{s}_k, s_j^a)| \\
&\leq \frac{\sum_{k \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \max_{h \in H} \psi(\kappa_\tau^a, \hat{s}_i^a, \bar{s}_h, \infty) + \frac{\sum_{k \in \bar{H}} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \max_{h \in \bar{H}} \psi(\kappa_\tau^a, \hat{s}_i^a, \bar{s}_h, \infty) \\
&\leq \frac{\sum_{k \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \psi_\delta^a + \frac{\sum_{k \in \bar{H}} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \max_h \psi(\kappa_\tau^a, \hat{s}_i^a, \bar{s}_h, \infty) \\
&\leq \frac{\sum_{k \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \psi_\delta^a + \frac{\sum_{k \in \bar{H}} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l=1}^m \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \psi_{\max}^a \\
&= \frac{\sum_{k \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) + \sum_{l \in \bar{H}} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \psi_\delta^a + \frac{\sum_{k \in \bar{H}} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) + \sum_{l \in \bar{H}} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l)} \psi_{\max}^a. \tag{2}
\end{aligned}$$

From the definition of  $\delta_a$  we can write

$$\mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k) \leq \frac{\alpha}{t} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w) \text{ if } \|\hat{s}_i^a - \bar{s}_k\| \geq \delta_a. \tag{3}$$

Now, let  $w = \operatorname{argmin}_k \|\hat{s}_i^a - \bar{s}_k\|$ . We know that  $\|\hat{s}_i^a - \bar{s}_w\| \leq \|\hat{s}_i^a - \bar{s}_*^a\|$ , and thus, from Assumption (iii), it follows that  $\mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w) \geq \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_*^a)$ . This fact together with (3) imply that

$$\mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k) \leq \frac{\alpha}{t} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w) \text{ if } \bar{s}_w \in \bar{H},$$

which allows us to write

$$\sum_{l \in \bar{H}} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) \leq \frac{\alpha |\bar{H}|}{t} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w). \tag{4}$$

Plugging (4) back into (2), we can write:

$$\|\mathbf{p}_i^a - \tilde{\mathbf{p}}_i^a\|_1 \leq \frac{\sum_{k \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) + \frac{\alpha |\bar{H}|}{t} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)} \psi_\delta^a + \frac{\frac{\alpha |\bar{H}|}{t} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)}{\sum_{l \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) + \frac{\alpha |\bar{H}|}{t} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)} \psi_{\max}^a \tag{5}$$

$$\leq \frac{\sum_{k \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) + \frac{\alpha}{t} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)} \psi_\delta^a + \frac{\frac{\alpha}{t} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)}{\sum_{l \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) + \frac{\alpha}{t} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)} \psi_{\max}^a \tag{6}$$

$$= \frac{\sum_{k \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)}{\sum_{l \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) + \alpha \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)} \psi_\delta^a + \frac{\alpha \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)}{\sum_{l \in H} \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) + \alpha \mathbf{k}_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)} \psi_{\max}^a, \tag{7}$$

where in (5) and (6) we used the fact that the coefficients multiplying  $\psi_\delta^a$  and  $\psi_{\max}^a$  define a convex combination, and we are increasing the weight of the latter. Noticing that

$$\frac{\alpha k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)}{\sum_{l \in H} k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_l) + \alpha k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)} \leq \frac{\alpha k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)}{k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w) + \alpha k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)} = \frac{\alpha}{1 + \alpha},$$

and applying the same reasoning to the coefficients of  $\psi_\delta^a$  and  $\psi_{\max}^a$  in (7), we can finally write

$$\|\mathbf{p}_i^a - \tilde{\mathbf{p}}_i^a\|_1 \leq \frac{1}{1 + \alpha} \psi_\delta^a + \frac{\alpha}{1 + \alpha} \psi_{\max}^a.$$

□

**Remarks:**

- $\psi_\delta^a \rightarrow \psi_{\max}^a$  as  $\alpha \rightarrow 0$ .
- There is an  $\alpha^* \in (0, 1]$  that minimizes the right-hand side of (1).

Let  $\tilde{\mathbf{v}} = \Gamma \mathbf{D} \bar{\mathbf{Q}}^*$ , where  $\Gamma$  is the ‘max’ operator applied row wise, that is,  $\tilde{v}_i = \max_a (\mathbf{D} \bar{\mathbf{Q}}^*)_{ia}$ . Recalling that  $\bar{\mathbf{d}}^*$  is the maximum distance from a sampled state  $\hat{s}_i^a$  to the closest representative state and that  $\bar{\tau}$  is the width of kernel  $k_{\bar{\tau}}$ , we present the following result:

**Proposition 1.** *For any  $\varepsilon > 0$ , there are  $\delta_1, \delta_2 > 0$  such that  $\|\hat{\mathbf{v}}^* - \tilde{\mathbf{v}}\|_\infty < \varepsilon$  if  $\bar{\mathbf{d}}^* < \delta_1$  and  $\bar{\tau} < \delta_2$ .*

*Proof.* We have previously showed that

$$\|\hat{\mathbf{v}}^* - \tilde{\mathbf{v}}\|_\infty \leq \frac{1}{1 - \gamma} \max_a \|\hat{\mathbf{r}}^a - \mathbf{D} \bar{\mathbf{r}}^a\|_\infty + \frac{1}{(1 - \gamma)^2} \left( \bar{C} \max_i (1 - \max_j d_{ij}) + \frac{\hat{C} \gamma}{2} \max_a \|\hat{\mathbf{P}}^a - \mathbf{D} \mathbf{K}^a\|_\infty \right), \quad (8)$$

where  $\|\cdot\|_\infty$  is the infinity norm,  $\hat{\mathbf{v}}^* \in \mathbb{R}^n$  is the optimal value function of KBRL’s MDP,  $\hat{C} = \max_{a,i} \hat{r}_i^a - \min_{a,i} \hat{r}_i^a$ ,  $\bar{C} = \max_{a,i} \bar{r}_i^a - \min_{a,i} \bar{r}_i^a$ , and  $\mathbf{K}^a$  is matrix  $\mathbf{K}$  with all elements equal to zero except for those corresponding to matrix  $\hat{\mathbf{K}}^a$  (see [1, 2] for details). Let  $\bar{\mathbf{r}} \equiv [(\mathbf{r}^1)^\top, (\mathbf{r}^2)^\top, \dots, (\mathbf{r}^{|A|})^\top]^\top \in \mathbb{R}^n$ , where  $\mathbf{r}^a \in \mathbb{R}^{n_a}$  is the vector composed of sample rewards  $r_i^a$ . Then,

$$\|\hat{\mathbf{r}}^a - \mathbf{D} \bar{\mathbf{r}}^a\|_\infty = \|\hat{\mathbf{P}}^a \bar{\mathbf{r}} - \mathbf{D} \hat{\mathbf{K}}^a \bar{\mathbf{r}}\|_\infty = \|\hat{\mathbf{P}}^a \bar{\mathbf{r}} - \mathbf{D} \mathbf{K}^a \bar{\mathbf{r}}\|_\infty = \|(\hat{\mathbf{P}}^a - \mathbf{D} \mathbf{K}^a) \bar{\mathbf{r}}\|_\infty \leq \|\hat{\mathbf{P}}^a - \mathbf{D} \mathbf{K}^a\|_\infty \|\bar{\mathbf{r}}\|_\infty, \quad (9)$$

where the equality  $\hat{\mathbf{r}}^a = \hat{\mathbf{P}}^a \bar{\mathbf{r}}$  is a consequence of the fact that KBRL’s reward function  $R^a(s, s')$  is independent of the start state  $s$  (see (1) in the main paper [2]). Thus, plugging (9) back into (8), it is clear that there is a  $\eta > 0$  such that  $\|\hat{\mathbf{v}}^* - \tilde{\mathbf{v}}\|_\infty < \varepsilon$  if  $\max_a \|\hat{\mathbf{P}}^a - \mathbf{D} \mathbf{K}^a\|_\infty < \eta$  and  $\max_i (1 - \max_j d_{ij}) < \eta$ . We start by showing that if  $\bar{\mathbf{d}}^*$  and  $\bar{\tau}$  are small enough, then  $\max_a \|\hat{\mathbf{P}}^a - \mathbf{D} \mathbf{K}^a\|_\infty < \eta$ . From Lemma 1 we know that, for any set of  $m \leq n$  representative states, and for any  $\alpha \in (0, 1]$ , the following must hold:

$$\max_a \|\mathbf{P}^a - \mathbf{D} \mathbf{K}^a\|_\infty \leq \frac{1}{1 + \alpha} \psi_\rho + \frac{\alpha}{1 + \alpha} \psi_{\text{MAX}},$$

where  $\psi_{\text{MAX}} = \max_{a,i,s} \psi(k_{\bar{\tau}}, \hat{s}_i^a, s, \infty)$  and  $\psi_\rho = \max_a \psi_\rho^a = \max_{a,i,j} \psi(k_{\bar{\tau}}, \hat{s}_i^a, \bar{s}_j, \rho^a)$ , with  $\rho^a = \rho(k_{\bar{\tau}}, \hat{s}_*^a, \bar{s}_*^a, \alpha/(n-1))$ . Note that  $\psi_{\text{MAX}}$  is independent of the representative states. Define  $\alpha$  such that  $\alpha/(1 + \alpha) \psi_{\text{MAX}} < \eta$ . We have to show that, if we define the representative states in such a way that  $\bar{\mathbf{d}}^*$  is small enough, and set  $\bar{\tau}$  accordingly, then we can make  $\psi_\rho < (1 - \alpha)\eta - \alpha \psi_{\text{MAX}} \equiv \eta'$ . From Property 4 we know that there is a  $\delta_1 > 0$  such that  $\psi_\rho < \eta'$  if  $\rho^a < \delta_1$  for all  $a \in A$ . From Property 1 we know that  $\rho^a \leq \rho(k_{\bar{\tau}}, \hat{s}_*^a, \bar{s}_*^a, \alpha/(n-1))$  for all  $a \in A$ . From Property 3 we know that, for any  $\varepsilon' > 0$ , there is a  $\delta' > 0$  such that  $\rho(k_{\bar{\tau}}, \hat{s}_*^a, \bar{s}_*^a, \alpha/(n-1)) < \bar{\mathbf{d}}^* + \varepsilon'$  if  $\bar{\tau} < \delta'$ . Therefore, if  $\bar{\mathbf{d}}^* < \delta_1$ , we can take any  $\varepsilon' < \delta_1 - \bar{\mathbf{d}}^*$  to have an upper bound  $\delta'$  for  $\bar{\tau}$ . It remains to show that there is a  $\delta > 0$  such that  $\min_i \max_j d_{ij} > 1 - \eta$  if  $\bar{\tau} < \delta$ . Recalling that  $d_{ij}^a = k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_j) / \sum_{k=1}^m k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_k)$ , let  $w = \arg \max_j k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_j)$ , and let  $y_i^a = k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_w)$  and  $\check{y}_i^a = \max_{j \neq w} k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_j)$ . Then, for any  $i$ ,

$$\max_j d_{ij}^a = \frac{y_i^a}{(y_i^a + \sum_{j \neq w} k_{\bar{\tau}}(\hat{s}_i^a, \bar{s}_j))} \geq \frac{y_i^a}{(y_i^a + (m-1)\check{y}_i^a)}.$$

From Assumption (v) and Property 3 we know that there is a  $\delta_i^a > 0$  such that there is a  $\delta_i^a > 0$  such that  $y_i^a > (m-1)(1 - \eta)\check{y}_i^a/\eta$  if  $\bar{\tau} < \delta_i^a$ . Thus, by making  $\delta = \min_{a,i} \delta_i^a$ , we can guarantee that  $\min_i \max_j d_{ij} > 1 - \eta$ . Finally, if we take  $\delta_2 = \min(\delta, \delta')$ , the result follows. □

**Remark:** If we define a ‘net’ over  $\mathbb{S}$  using the representative states, then we know that  $\bar{\mathbf{d}}^*$  is smaller than the resolution of the net.

## References

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