

computational cost becomes a function of m only. In particular, the cost of solving \bar{M} through dynamic programming becomes polynomial in m instead of n : while one application of \hat{T} , the Bellman operator of \hat{M} , is $O(n\hat{n}|A|)$, the computation of \bar{T} is $O(m^2|A|)$. Therefore, KBSF’s time and memory complexities are only linear in n .

We note that, in practice, KBSF’s computational requirements can be reduced even further if one enforces the kernels κ_τ^a and $\bar{\kappa}_\tau$ to be sparse. In particular, given a fixed \bar{s}_i , instead of computing $\bar{\kappa}_\tau(\bar{s}_i, s_j^a)$ for $j = 1, 2, \dots, n_a$, one can evaluate the kernel on a pre-specified neighborhood of \bar{s}_i only. Assuming that $\bar{\kappa}_\tau(\bar{s}_i, s_j^a)$ is zero for all s_j^a outside this region, one avoids not only computing the kernel but also storing the resulting values (the same reasoning applies to the computation of $\kappa_\tau(\hat{s}_i^a, \bar{s}_j)$ for a fixed \hat{s}_i^a).

4.1 A closer look at KBSF’s approximation

As outlined in Section , KBRL defines the probability of a transition from state \hat{s}_i^b to state \hat{s}_k^a as being $\kappa_\tau^a(\hat{s}_i^b, s_k^a)$, where $a, b \in A$ (see Figure 2a). Note that the kernel κ_τ^a is computed with the initial state s_k^a , and not \hat{s}_k^a itself. The intuition behind this is simple: since we know the transition $s_k^a \xrightarrow{a} \hat{s}_k^a$ has occurred before, the more “similar” \hat{s}_i^b is to s_k^a , the more likely the transition $\hat{s}_i^b \xrightarrow{a} \hat{s}_k^a$ becomes (Ormoneit and Sen, 2002).

From (13), it is clear that the computation of matrices \mathbf{K}^a performed by KBSF follows the same reasoning underlying the computation of KBRL’s matrices $\hat{\mathbf{P}}^a$; in particular, $\kappa_\tau^a(\bar{s}_j, s_k^a)$ gives the probability of a transition from \bar{s}_j to \hat{s}_k^a . However, when we look at matrix \mathbf{D} things are slightly different: here, the probability of a “transition” from \hat{s}_i^b to representative state \bar{s}_j is given by $\bar{\kappa}_\tau(\hat{s}_i^b, \bar{s}_j)$ —a computation that involves \bar{s}_j itself. If we were to strictly adhere to KBRL’s logic when computing the transition probabilities to the representative states \bar{s}_j , the probability of transitioning from \hat{s}_i^b to \bar{s}_j upon executing action a should be a function of \hat{s}_i^b and a state s' from which we knew a transition $s' \xrightarrow{a} \bar{s}_j$ had occurred. In this case we would end up with one matrix \mathbf{D}^a for each action $a \in A$. Note though that this formulation of the method is not practical, because the computation of the matrices \mathbf{D}^a would require a transition $(\cdot) \xrightarrow{a} \bar{s}_j$ for each $a \in A$ and each $\bar{s}_j \in \bar{\mathcal{S}}$. Clearly, such a requirement is hard to fulfill even if we have a generative model available to generate sample transitions.

In this section we provide an interpretation of the approximation computed by KBSF that supports our definition of matrix \mathbf{D} . We start by looking at how KBRL constructs the matrices $\hat{\mathbf{P}}^a$. As shown in Figure 2a, for each action $a \in A$ the state \hat{s}_i^b has an associated stochastic vector $\hat{\mathbf{p}}_j^a \in \mathbb{R}^{1 \times n}$ whose nonzero entries correspond to the kernel $\kappa_\tau^a(\hat{s}_i^b, \cdot)$ evaluated at $s_k^a, k = 1, 2, \dots, n_a$. Since we are dealing with a continuous state space, it is possible to compute an analogous vector for any $s \in \mathcal{S}$ and any $a \in A$. Focusing on the nonzero entries of $\hat{\mathbf{p}}_j^a$, we define the function

$$\begin{aligned} \hat{\mathcal{P}}_{S^a} : \mathcal{S} &\mapsto \mathbb{R}^{1 \times n_a} \\ \hat{\mathcal{P}}_{S^a}(s) = \hat{\mathbf{p}}^a &\iff \hat{p}_i^a = \kappa_\tau^a(s, s_i^a) \text{ for } i = 1, 2, \dots, n_a. \end{aligned} \quad (16)$$

Clearly, full knowledge of the function $\hat{\mathcal{P}}_{S^a}$ allows for an exact computation of KBRL’s transition matrix $\hat{\mathbf{P}}^a$. Now suppose we do not know $\hat{\mathcal{P}}_{S^a}$ and we want to compute an