

td, the standard LST D algorithm was reviewed and two versions of the differential TD learning algorithm were presented. A cost value function [?, ?]. However, such choices are heavily problem – dependent and no standard method exist. In most traditional examples of TD learning, a predetermined set of basis functions. The chosen function class may not be rich enough to give a good approximation of the value function.

td in a reproducing kernel Hilbert space (RKHS) setting. It is organized as follows –
 Ins : rkhs_basics, a concise introduction to kernel functions and the RKHS theory is provided. A more detailed discussion of its
 a brief introduction is provided in ins : erm. Obtaining solutions to such problems is made possible via the classical representer theorem problem in \mathbb{R}^2

td grad TD norm error of approximating the gradient of the solution to Poisson's equation is reformulated as an equivalent ER optimal solution that lies on a subspace of the original RKHS is also presented. We provide a short review of an error analysis ap

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$$\begin{aligned} & \mathbb{R} \rightarrow \\ & \mathbb{R} \in \\ & \mathbb{R} \in \\ & \{x^i\} \in: \\ & \frac{1}{N} < \\ & \frac{1}{N} < \\ & \frac{1}{N} < \\ & \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j (x^i, x^j) \geq 0, \forall \alpha_i \in \mathbb{R}, \forall x^i \in \end{aligned}$$

(1)

$$f(\cdot) = \sum_{i=1}^N \alpha_i (x^i, \cdot),$$

(2)

$$\begin{aligned} & \mathbb{R}, \alpha_i \in \\ & \mathbb{R}, \{x^i\} \in: \\ & \frac{1}{N} < \\ & \frac{1}{N} < \\ & \frac{1}{N} < \\ & \sum_{j=1}^M g(x^j, \cdot), \end{aligned}$$

(3)

$$\begin{aligned} & \mathbb{R} \in \\ & \{x^j\}_{j=1}^M \\ & f, g \in \mathbb{R}^0 \\ & \langle f, g \rangle = \sum_{i=1}^N \sum_{j=1}^M \alpha_{ij} (x^i, x^j). \end{aligned}$$

(4)

$$\langle f, g \rangle = \sum_{i=1}^N \alpha_i g(x^i) = \sum_{j=1}^N f(x^j)$$

(5)

$$\begin{aligned} & \text{inner product and is given by, } \langle (x, \cdot), f(\cdot) \rangle = \\ & f(x) \forall x \in \\ & , \forall f \in \mathbb{R}^0 \\ & \cdot \end{aligned}$$

(6)

$$\langle x, x' \rangle = (x, x') = (x', x) = \langle x', x \rangle.$$

(7)

$$\begin{aligned} & f_{\text{rkhs}}, \text{ that are endowed with the inner product defined in } \text{rkhs_inner_product} \text{ (denoted as } \langle \cdot, \cdot \rangle) \\ & \|f\| = \sqrt{\langle f, f \rangle} \\ & \mathbb{R} \rightarrow \\ & \mathbb{R}^2 \\ & L^2 \\ & f \in \\ & \{f_n\} \subset \\ & \|f_n - \\ & f\| \rightarrow 0 \\ & \infty \\ & x \in \\ & \lim_{n \rightarrow \infty} f_n(x) = \lim_{n \rightarrow \infty} \langle x, f_n \rangle = \langle x, f \rangle = f(x) \end{aligned}$$