

## Supplementary Material

### A. Proof of Theorem 4.1

*Proof.* When  $L$  is finite, the inner product between the feature representation is given by

$$\begin{aligned} \mathbf{h}_{\mathbf{x}}^T \mathbf{h}_{\mathbf{y}} &= \frac{1}{L} (W^T A^T \mathbf{x})_+^T (W^T A^T \mathbf{y})_+ \\ &= \frac{1}{L} (\mathbf{x}^T A W)_+ (W^T A^T \mathbf{y})_+ \\ &= \frac{1}{L} \sum_{l=1}^L (\mathbf{x}^T A w_l)_+ (\mathbf{y}^T A w_l)_+ \end{aligned}$$

Since  $w_l$ ,  $1 \leq l \leq L$  is a random vector, the above quantity is the empirical mean of  $L$  random variables,  $z_1, \dots, z_L$ , where  $z_l = (\mathbf{x}^T A w_l)_+ (\mathbf{y}^T A w_l)_+$ . Furthermore since  $w_l$ 's are independent and identically distributed,  $z_l$ 's being functions of  $w_l$ 's are also independent and identically distributed. Hence, by law of large numbers, as  $L \rightarrow +\infty$ , the empirical mean of  $z_l$ 's converges to the true mean, that is,

$$\lim_{L \rightarrow \infty} \mathbf{h}_{\mathbf{x}}^T \mathbf{h}_{\mathbf{y}} \quad (10)$$

$$= \lim_{L \rightarrow +\infty} \frac{1}{L} \sum_{l=1}^L (\mathbf{x}^T A w_l)_+ (\mathbf{y}^T A w_l)_+ \quad (11)$$

$$= \int_{w \in \mathbb{R}^d} (\mathbf{x}^T A w)_+ (\mathbf{y}^T A w)_+ p(w) dw \quad (12)$$

$$= \frac{1}{(2\pi)^{\frac{d}{2}}} \int_{w \in \mathbb{R}^d} (\mathbf{x}^T A w)_+ (\mathbf{y}^T A w)_+ e^{-\frac{\|w\|^2}{2}} dw \quad (13)$$

$$= \frac{1}{2\pi} \|A^T \mathbf{x}\| \|A^T \mathbf{y}\| (\sin \theta_A + (\pi - \theta_A) \cos \theta_A), \quad (14)$$

where  $\theta_A = \cos^{-1} \frac{\mathbf{x}^T A A^T \mathbf{y}}{\|A \mathbf{x}\| \|A \mathbf{y}\|}$ . Here, the last equation follows from the derivation of arc-cosine kernel by [Cho & Saul \(2010\)](#).  $\square$

### B. Proof of Theorem 5.1

*Proof.* After  $T$  iteration of Algorithm 1, the approximate kernel matrix  $k_{ap}(\mathbf{x}, \mathbf{y})$  is given by

$$\begin{aligned} k_{ap}(\mathbf{x}, \mathbf{y}) &= \frac{1}{T} \sum_{t=1}^T \frac{1}{L I^2} \sum_{i=1}^I \sum_{j=1}^I \sum_{\ell=1}^L (p_i^T A w_{t\ell})_+ (q_j^T A w_{t\ell})_+ , \\ &= \frac{1}{T L} \sum_{t,l} \sum_{i,j} (p_i^T A w_{t\ell})_+ (q_j^T A w_{t\ell})_+ . \end{aligned}$$

Furthermore, the mean and variance of the approximate

kernel after  $T$  iterations is given by

$$\begin{aligned} m(\mathbf{x}, \mathbf{y}) &= \frac{1}{T L I^2} \sum_{t,l} \sum_{i,j} \mathbb{E}[(p_i^T A w_{t\ell})_+ (q_j^T A w_{t\ell})_+] \\ &= \frac{1}{T L I^2} \sum_{t,l} \sum_{i,j} k_{\Sigma}(p_i, q_j) \\ &= \frac{1}{I^2} \sum_{i,j} k_{\Sigma}(p_i, q_j) \\ &= k(\mathbf{x}, \mathbf{y}). \\ v(\mathbf{x}, \mathbf{y}) &= \frac{1}{T^2 L^2 I^2} \sum_{t,l} \text{var}\left(\frac{1}{I^2} \sum_{i,j} (p_i^T A w_{t\ell})_+ (q_j^T A w_{t\ell})_+\right) \\ &\leq \frac{1}{T^2 L^2 I^2} \sum_{t,l} \sum_{i,j} \text{var}((p_i^T A w_{t\ell})_+ (q_j^T A w_{t\ell})_+) \\ &= \frac{1}{T L I^2} \sum_{i,j} \text{var}((p_i^T A w)_+ (q_j^T A w)_+) \end{aligned}$$

Since  $\text{var}(X) = \mathbb{E}X^2 - (\mathbb{E}X)^2 \leq \mathbb{E}X^2$ ,  $\text{var}((p_i^T A w)_+ (q_j^T A w)_+) \leq \mathbb{E}[(p_i^T A w)_+^2 (q_j^T A w)_+^2]$ . From equation (7) of [Cho et al. \(?\)](#), the same quantity can be rewritten as

$$\begin{aligned} &\mathbb{E}[(p_i^T A w)_+^2 (q_j^T A w)_+^2] \\ &= \|A p_i\|^2 \|A q_j\|^2 \frac{(3 \sin \theta \cos \theta + (\pi - \theta)(1 + 2 \cos^2 \theta))}{2\pi} \\ &\leq 2 \|A p_i\|^2 \|A q_j\|^2 . \end{aligned}$$

Hence, by applying Chebyshev's inequality to the quantity  $k_{ap}(\mathbf{x}, \mathbf{y})$ , we get

$$\begin{aligned} &P(|k_{ap}(\mathbf{x}, \mathbf{y}) - k(\mathbf{x}, \mathbf{y})| \geq \epsilon) \\ &\leq 2 \frac{1}{T L I^2 \epsilon^2} \sum_{i=1}^I \sum_{j=1}^I \|A p_i\|^2 \|A q_j\|^2 . \end{aligned}$$

Hence, as  $T \rightarrow \infty$ , approximate kernel entry converges in probability to the exact kernel entry. Rewriting the above statement, we can say that with probability at least  $1 - \delta$ .

$$\begin{aligned} &|k_{ap}(\mathbf{x}, \mathbf{y}) - k(\mathbf{x}, \mathbf{y})| \\ &\leq \sqrt{\frac{2}{T L \delta}} \sqrt{\frac{1}{I^2} \sum_{i=1}^I \sum_{j=1}^I \|A p_i\|^2 \|A q_j\|^2} \end{aligned}$$

$\square$