
Supplementary material for Reducing statistical time-series problems to binary classification

Theorem 1. Let $\mathbf{H} = (\mathcal{H}_1, \mathcal{H}_2, \dots)$, $\mathcal{H}_k \subset \mathcal{X}^k$, $k \in \mathbb{N}$ be a sequence of separable sets of indicator functions of finite VC dimension such that \mathcal{H}_k generates $\mathcal{F}_{\mathcal{X}^k}$. Then, for every stationary ergodic time series distributions ρ_X and ρ_Y generating samples $X_{1..n}$ and $Y_{1..m}$ we have

$$\lim_{n, m \rightarrow \infty} \hat{D}_{\mathbf{H}}(X_{1..n}, Y_{1..m}) = D_{\mathbf{H}}(\rho_X, \rho_Y) \quad (1)$$

Proof. As is established in [2], under the conditions of the theorem we have

$$\lim_{n \rightarrow \infty} \sup_{h \in \mathcal{H}_k} \frac{1}{n - k + 1} \sum_{i=1}^{n-k+1} h(X_{i..i+k-1}) = \sup_{h \in \mathcal{H}_k} \mathbf{E}_{\rho_X} h(X_1, \dots, X_k) \quad \rho_X\text{-a.s.} \quad (2)$$

for all $k \in \mathbb{N}$, and likewise for ρ_Y . Fix an $\varepsilon > 0$. We can find a $T \in \mathbb{N}$ such that

$$\sum_{k > T} w_k \leq \varepsilon. \quad (3)$$

Note that T depends only on ε . Moreover, as follows from (2), for each $k = 1..T$ we can find an N_k such that

$$\left| \sup_{h \in \mathcal{H}_k} \frac{1}{n - k + 1} \sum_{i=1}^{n-k+1} h(X_{i..i+k-1}) - \sup_{h \in \mathcal{H}_k} \mathbf{E}_{\rho_X} h(X_{1..k}) \right| \leq \varepsilon/T \quad (4)$$

Let $N_k := \max_{i=1..T} N_i$ and define analogously M for ρ_Y . Thus, for $n \geq N$, $m \geq M$ we have

$$\begin{aligned} & \hat{D}_{\mathbf{H}}(X_{1..n}, Y_{1..m}) \\ & \leq \sum_{k=1}^T w_k \sup_{h \in \mathcal{H}_k} \left| \frac{1}{n - k + 1} \sum_{i=1}^{n-k+1} h(X_{i..i+k-1}) - \frac{1}{m - k + 1} \sum_{i=1}^{m-k+1} h(Y_{i..i+k-1}) \right| + \varepsilon \\ & \leq \sum_{k=1}^T w_k \sup_{h \in \mathcal{H}_k} \left\{ \left| \frac{1}{n - k + 1} \sum_{i=1}^{n-k+1} h(X_{i..i+k-1}) - \mathbf{E}_{\rho_1} h(X_{1..k}) \right| \right. \\ & \quad \left. + |\mathbf{E}_{\rho_1} h(X_{1..k}) - \mathbf{E}_{\rho_2} h(Y_{1..k})| \right. \\ & \quad \left. + \left| \mathbf{E}_{\rho_2} h(Y_{1..k}) - \frac{1}{m - k + 1} \sum_{i=1}^{m-k+1} h(Y_{i..i+k-1}) \right| \right\} + \varepsilon \\ & \leq 3\varepsilon + D_{\mathbf{H}}(\rho_X, \rho_Y), \end{aligned}$$

where the first inequality follows from the definition of $\hat{D}_{\mathbf{H}}$ (2) and from (3) and the last inequality follows from (4). Since ε was chosen arbitrary the statement follows. \square

Lemma 1.1. Let two samples $X_{1..n}$ and $Y_{1..m}$ be generated by stationary distributions ρ_X and ρ_Y whose β -mixing coefficients satisfy $\beta(\rho, t) \leq \gamma^t$ for some $\gamma < 1$. Let \mathcal{H}_k , $k \in \mathbb{N}$ be some sets of indicator functions on \mathcal{X}^k whose VC dimension d_k is finite and non-decreasing with k . Then

$$P(|\hat{D}_{\mathbf{H}}(X_{1..n}, Y_{1..m}) - D_{\mathbf{H}}(\rho_X, \rho_Y)| > \varepsilon) \leq 2\Delta(\varepsilon/4, n') \quad (5)$$

where $n' := \min\{n_1, n_2\}$, the probability is with respect to $\rho_X \times \rho_Y$ and

$$\Delta(\varepsilon, n) := -\log \varepsilon (n \gamma^{\sqrt{n} + \log(\varepsilon)} + 8n^{(d - \log \varepsilon + 1)/2} e^{-\sqrt{n}\varepsilon^2/8}). \quad (6)$$

Proof. Note that $\sum_{k=-\log \varepsilon/2}^{\infty} w_k < \varepsilon/2$. Using this and the definitions (1) and (2) of $D_{\mathbf{H}}$ and $\hat{D}_{\mathbf{H}}$ we obtain

$$P(|\hat{D}_{\mathbf{H}}(X_{1..n_1}, Y_{1..n_2}) - D_{\mathbf{H}}(\rho_X, \rho_Y)| > \varepsilon) \leq \sum_{k=1}^{-\log(\varepsilon/2)} (q_n(\rho_X, \mathcal{H}_k, \varepsilon/4) + q_n(\rho_Y, \mathcal{H}_k, \varepsilon/4)),$$

which, together with (6) implies the statement. \square