

Supplement to “A model-free feature screening approach based on kernel density estimation”

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The supplementary gives the proof of Proposition 2.1:

Proof. (1) If X_j is independent of Y , then X_j will be independent for any H , and so $f(X|H = l) = f(X)$, for any $l \in \{1, \dots, S\}$, thus $\omega_j^S = 0$. Now suppose $\omega_j^S = 0$ for all choices of \mathcal{S} , say $|g_l^o(x_j) - g_m^o(x_j)| = 0$ a.s. for any $l, m \in \{1, \dots, S\}$. We consider $H = 1$ if $Y \leq y$ and $H = 2$ otherwise for any y . Because $\omega_j^S = 0$ and X is independent of H , $f(X_j|Y \leq y) = f(X_j|Y > y)$ for all y , that is, if $\Pr(Y \leq y) = 0$ or $\Pr(Y > y) = 0$, the result holds naturally and if $\Pr(Y \leq y) > 0$ and $\Pr(Y > y) > 0$, then

$$\begin{aligned} \frac{f(X_j, Y \leq y)}{\Pr(Y \leq y)} &= \frac{f(X_j, Y > y)}{1 - \Pr(Y \leq y)} \\ \Leftrightarrow (f(X_j, Y \leq y) + f(X_j, Y > y)) \Pr(Y \leq y) &= f(X_j, Y \leq y) \\ \Leftrightarrow \Pr(Y \leq y) f(X_j) &= f(X_j, Y \leq y) \\ \Leftrightarrow \Pr(Y \leq y) f(X_j) &= f(X_j|Y \leq y) \Pr(Y \leq y) \\ \Leftrightarrow f(X_j) &= f(X_j|Y \leq y) \text{ for any } y. \end{aligned}$$

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Consequently, X_j is independent of Y .

(2) Suppose $\omega_j^S = 0$, then X_j is independent of H according to the previous proposition. Therefore, $\Pr(Y \leq a_1 | X_j) = \Pr(H = 1 | X_j) = \Pr(H = 1)$ is a constant unrelated to x_j , which contradicts with our assumption. As a result, we must have ω_j^S .

(3) For the last conclusion, we define

$$\omega_j^* = \sup_{y_1, y_2} \int |g_{y_1}^o(x_j) - g_{y_2}^o(x_j)| dx_j, \quad (1)$$

where

$$\begin{aligned} g_{y_1}^o(x_j) &= \begin{cases} f(x_j | Y = y_1), & x_j \in \Omega_{y_1} \\ 0, & x_j \in \Omega_{y_2} \setminus \Omega_{y_1}. \end{cases} \\ g_{y_2}^o(x_j) &= \begin{cases} f(x_j | Y = y_2), & x_j \in \Omega_{y_2} \\ 0, & x_j \in \Omega_{y_1} \setminus \Omega_{y_2}. \end{cases} \end{aligned}$$

and

$$\omega_j^S = \max_{l, m} \int_{\Omega_l \cup \Omega_m} |g_l^o(x_j) - g_m^o(x_j)| dx_j, \quad (2)$$

where

$$\begin{aligned} g_l^o(x_j) &= \begin{cases} f(x_j | H = l), & x_j \in \Omega_l \\ 0, & x_j \in \Omega_m \setminus \Omega_l \end{cases} \\ g_m^o(x_j) &= \begin{cases} f(x_j | H = m), & x_j \in \Omega_m \\ 0, & x_j \in \Omega_l \setminus \Omega_m. \end{cases} \end{aligned}$$

It is noteworthy that $g_{y_1}^o$ and $g_{y_2}^o$ corresponds to the random variable Y , but g_l^o and g_m^o corresponds to the random variable H , however we abuse the notation a little by writing the g^o for both two cases. We can obtain $\omega_j^* > 0$ in that X_j is not independent of Y , $\omega_j^* > 0$. So we just need to prove $\omega_j^S \rightarrow \omega_j^*$ as $S \rightarrow \infty$. By the definition ω_j^* , for $\forall \varepsilon > 0$, there exists y_1^*, y_2^* such that

$$|\omega_j^* - \int |g_{y_1^*}^o(x_j) - g_{y_2^*}^o(x_j)| dx_j| < \varepsilon.$$

Because $f(x_j|y)$ is continuous in y and is bounded by a fixed constant M and

$$\int |g_{y_1}^o(x_j) - g_{y_2}^o(x_j)| dx_j \leq \int [|g_{y_1}^o(x_j)| + |g_{y_2}^o(x_j)|] dx_j = 2.$$

there exists $\delta > 0$ such that $\int |g_y^o(x_j) - g_{y_1^*}^o(x_j)| dx_j$ for any $|y - y_1^*| < \delta$. Take $\Delta = \Pr(|y - y_1^*| < \delta)$, due to $\max_{l=1, \dots, S} \Pr(H = l) \rightarrow 0$, there exists S_0 such that $\Pr(H = l) \leq \frac{\Delta}{2}$ for $S > S_0$. In such cases, there exists $[a_{l_1}, a_{l_1+1}) \subset (y_1^* - \delta, y_1^* + \delta)$.

We can easily prove that

$$\int |g_{l_1}^o(x_j) - g_{y_1^*}^o(x_j)| dx_j \leq \varepsilon \quad (3)$$

Similarly, there exists l_2 such that

$$\int |g_{l_2}^o(x_j) - g_{y_2^*}^o(x_j)| dx_j \leq \varepsilon \quad (4)$$

In addition,

$$\int |g_{l_1}^o(x_j) - g_{l_2}^o(x_j)| dx_j \leq \omega_j^S \leq \omega_j^*$$

Hence,

$$\begin{aligned} |\omega_j^* - \omega_j^S| &= \omega_j^* - \omega_j^S \\ &\leq \int |g_{y_1^*}^o(x_j) - g_{y_2^*}^o(x_j)| dx_j + \varepsilon - \int |g_{l_1}^o(x_j) - g_{l_2}^o(x_j)| dx_j \\ &\leq \int |g_{y_1^*}^o(x_j) - g_{y_2^*}^o(x_j) - g_{l_1}^o(x_j) + g_{l_2}^o(x_j)| dx_j + \varepsilon \\ &\leq \int [|g_{l_1}^o(x_j) - g_{y_1^*}^o(x_j)| + |g_{l_2}^o(x_j) - g_{y_2^*}^o(x_j)|] dx_j + \varepsilon \\ &= \sum_{i=1,2} \int |g_{l_i}^o(x_j) - g_{y_i^*}^o(x_j)| dx_j + \varepsilon \\ &\leq 3\varepsilon. \end{aligned}$$

Due to ε is arbitrary, the conclusion follows. \square