

# Appendix to “Fast Nonparametric Quantile Regression with Arbitrary Smoothing Methods” published in the Journal of Computational and Graphical Statistics

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## A Proof of Proposition 1

Let  $\phi_\tau(x) = \rho'_\tau(x)$  and  $\psi_\tau(x) = \rho'_{\tau,c}(x)$ . By the definition of quantile and pseudo quantile, it follows that

$$\psi_\tau(y - \alpha^*)f(y)dy = 0 \quad \text{and} \quad \phi_\tau(y - \alpha_0)f(y)dy = 0. \quad (12)$$

Next we calculate a bound for

$$\int_{\mathbb{R}} \{\psi_\tau(y - \alpha) - \phi_\tau(y - \alpha)\} f(y) dy.$$

With the substitution  $u = y - \alpha$  we have

$$\begin{aligned} \int_{\mathbb{R}} \{\psi_\tau(u) - \phi_\tau(u)\} f(u + \alpha) du &= \int_{-c}^c \{\psi_\tau(u) - \phi_\tau(u)\} f(u + \alpha) du \\ &\leq \int_{-c}^c \{\psi_\tau(u) - \phi_\tau(u)\} du \cdot \sup |f| \\ &= \left\{ \frac{c}{2}\tau + \frac{c}{2}(1 - \tau) \right\} \sup |f| = \frac{c}{2} \sup |f|. \end{aligned} \quad (13)$$

To derive the bound of interests, we consider

$$\begin{aligned} &\int_{\mathbb{R}} \{\psi_\tau(y - \alpha^*) - \phi_\tau(y - \alpha^*)\} f(y) dy \\ &= \int_{\mathbb{R}} \psi_\tau(y - \alpha^*) f(y) dy - \int_{\mathbb{R}} \phi_\tau(y - \alpha^*) f(y) dy. \end{aligned}$$

Given (12), it follows that

$$\begin{aligned} \int_{\mathbb{R}} \{\psi_\tau(y - \alpha^*) - \phi_\tau(y - \alpha^*)\} f(y) dy &= - \int_{\mathbb{R}} \phi_\tau(y - \alpha^*) f(y) dy \\ &= \int_{-\infty}^{\alpha^*} (1 - \tau) f(y) dy - \int_{\alpha^*}^{\infty} \tau f(y) dy. \end{aligned}$$

Without loss of generality, we assume  $\alpha_0 < \alpha^*$ . Then, by the following fact which can be derived by (12)

$$\int_{\alpha_0}^{\infty} \tau f(y) dy = \int_{-\infty}^{\alpha_0} (1 - \tau) f(y) dy, \quad (14)$$

we obtain

$$\begin{aligned} \int_{-\infty}^{\alpha^*} (1 - \tau) f(y) dy - \int_{\alpha^*}^{\infty} \tau f(y) dy &= \int_{-\infty}^{\alpha_0} (1 - \tau) f(y) dy + \int_{\alpha_0}^{\alpha^*} (1 - \tau) f(y) dy \\ &\quad - \left\{ \int_{\alpha_0}^{\infty} \tau f(y) dy - \int_{\alpha_0}^{\alpha^*} \tau f(y) dy \right\} \\ &= \int_{\alpha_0}^{\alpha^*} (1 - \tau) f(y) dy + \int_{\alpha_0}^{\alpha^*} \tau f(y) dy \\ &= \int_{\alpha_0}^{\alpha^*} f(y) dy = F(\alpha^*) - F(\alpha_0). \end{aligned} \quad (15)$$

Finally, by applying the general bound of (13) to (15), we establish the proposition.  $\square$

## B Proof of Proposition 2

Suppose that  $\alpha_0$  is the optimal solution of (4). For a sufficiently small  $c$ , the increment resulted from subtracting the minimizer  $\alpha_0$  by  $\delta_\alpha$  can be expressed as

$$\begin{aligned} &\sum_{i=1}^n \rho_{\tau,c}(y_i - \alpha_0 + \delta_\alpha) - \sum_{i=1}^n \rho_{\tau,c}(y_i - \alpha_0) \\ &= \sum_{i=1}^n \left[ \tau((y_i - \alpha_0 + \delta_\alpha) - \frac{1}{2}c) \mathbf{I}(c \leq y_i - \alpha_0 + \delta_\alpha) - \tau((y_i - \alpha_0) - \frac{1}{2}c) \mathbf{I}(c \leq y_i - \alpha_0) \right] \\ &\quad + \sum_{i=1}^n \left[ \frac{1}{2} \tau(y_i - \alpha_0 + \delta_\alpha)^2 / c \mathbf{I}(0 \leq y_i - \alpha_0 + \delta_\alpha < c) - \frac{1}{2} \tau(y_i - \alpha_0)^2 / c \mathbf{I}(0 \leq y_i - \alpha_0 < c) \right] \\ &\quad + \sum_{i=1}^n \left[ \frac{1}{2} (1 - \tau)(y_i - \alpha_0 + \delta_\alpha)^2 / c \mathbf{I}(-c \leq y_i - \alpha_0 + \delta_\alpha < 0) \right. \\ &\quad \quad \left. - \frac{1}{2} (1 - \tau)(y_i - \alpha_0)^2 / c \mathbf{I}(-c \leq y_i - \alpha_0 < 0) \right] \\ &\quad + \sum_{i=1}^n \left[ (\tau - 1)((y_i - \alpha_0 + \delta_\alpha) + \frac{1}{2}c) \mathbf{I}(y_i - \alpha_0 + \delta_\alpha < -c) \right. \\ &\quad \quad \left. - (\tau - 1)((y_i - \alpha_0) + \frac{1}{2}c) \mathbf{I}(y_i - \alpha_0 < -c) \right]. \end{aligned}$$

Now we examine this one term at a time. The first term is

$$\sum_{i=1}^n \left[ \tau((y_i - \alpha_0 + \delta_\alpha) - \frac{1}{2}c)I(c \leq y_i - \alpha_0 + \delta_\alpha) - \tau((y_i - \alpha_0) - \frac{1}{2}c)I(c \leq y_i - \alpha_0) \right] = \tau\delta_\alpha n_1, \quad (16)$$

where  $n_1$  is the number of terms with  $y_i \geq \alpha_0 + c$ . Next, the second term becomes, for  $0 \leq y_i - \alpha_0 < c$ ,

$$\begin{aligned} & \sum_{i=1}^n \left[ \frac{1}{2}\tau(y_i - \alpha_0 + \delta_\alpha)^2/cI(0 \leq y_i - \alpha_0 + \delta_\alpha < c) - \frac{1}{2}\tau(y_i - \alpha_0)^2/cI(0 \leq y_i - \alpha_0 < c) \right] \\ &= \frac{\tau}{2c} \sum_{i=1}^n \left[ (y_i - \alpha_0 + \delta_\alpha)^2 - (y_i - \alpha_0)^2 \right] \\ &\approx \delta_\alpha \frac{\tau}{c} \sum_{i=1}^n (y_i - \alpha)I(0 \leq y_i - \alpha_0 < c). \end{aligned} \quad (17)$$

Since  $\sum_{i=1}^n (y_i - \alpha)I(0 \leq y_i - \alpha_0 < c) \leq n_2 c$ , where  $n_2$  is the number of terms with  $0 \leq y_i < \alpha_0 + c$ , it follows that the second term of (17) is less than or equal to  $n_2 \delta_\alpha \tau$ . That is,

$$\delta_\alpha \frac{\tau}{c} \sum_{i=1}^n (y_i - \alpha)I(0 \leq y_i - \alpha_0 < c) = n_2 \delta_\alpha \tau - \kappa, \quad (18)$$

where  $\kappa(< \infty)$  represents the difference between (17) and  $n_2 \delta_\alpha \tau$ . Similarly, the third term can be written as

$$\begin{aligned} & \sum_{i=1}^n \left[ \frac{1}{2}(1 - \tau)(y_i - \alpha_0 + \delta_\alpha)^2/cI(-c \leq y_i - \alpha_0 + \delta_\alpha < 0) \right. \\ & \quad \left. - \frac{1}{2}(1 - \tau)(y_i - \alpha_0)^2/cI(-c \leq y_i - \alpha_0 < 0) \right] \\ & \approx (\tau - 1)\delta_{\alpha_0} n_3 + \kappa', \end{aligned} \quad (19)$$

where  $n_3$  denotes the number of terms with  $-c \leq y_i - \alpha_0 < 0$  and  $\kappa'$  is a finite constant which is the difference between the third term and  $(\tau - 1)\delta_{\alpha_0} n_3$ . Finally, we obtain the fourth term as

$$\begin{aligned} & \sum_{i=1}^n \left[ (\tau - 1)((y_i - \alpha_0 + \delta_\alpha) + \frac{1}{2}c)I(y_i - \alpha_0 + \delta_\alpha < -c) \right. \\ & \quad \left. - (\tau - 1)((y_i - \alpha_0) + \frac{1}{2}c)I(y_i - \alpha_0 < -c) \right] \\ &= n_4(\tau - 1)\delta_\alpha, \end{aligned} \quad (20)$$

where  $n_4$  denotes the number of terms with  $y_i < \alpha_0 - c$ . Hence, by combining (16)-(20), we obtain

$$\begin{aligned} & \sum_{i=1}^n \rho_{\tau,c}(y_i - \alpha_0 + \delta_\alpha) - \sum_{i=1}^n \rho_{\tau,c}(y_i - \alpha_0) \\ &= \tau\delta_\alpha n_1 + \tau\delta_\alpha n_2 - \kappa + (\tau - 1)\delta_\alpha n_3 + \kappa' + (\tau - 1)\delta_\alpha n_4. \end{aligned}$$

Let  $\zeta = \kappa' - \kappa$ . Note that with a sufficiently small  $c$ ,  $\zeta$  is close to zero. In the median case of  $\tau = 0.5$ ,  $\zeta$  is exactly equal to zero. Define  $n_+$  as the number of positive terms and  $n_-$  as the number of negative terms. Note that  $n = n_+ + n_-$ . Then

$$\begin{aligned} & \sum_{i=1}^n \rho_{\tau,c}(y_i - \alpha_0 + \delta_\alpha) - \sum_{i=1}^n \rho_{\tau,c}(y_i - \alpha_0) \\ &= \tau\delta_\alpha(n_1 + n_2) + (\tau - 1)\delta_\alpha(n_3 + n_4) + \zeta \\ &= \delta_\alpha[\tau n_+ + (\tau - 1)n_- + \Delta] \\ &= \delta_\alpha[\tau n + \Delta - n_-], \end{aligned} \tag{21}$$

where  $\Delta = \zeta/\delta_\alpha$  which is negligible with a sufficiently small  $c$ . Hence, by requiring that (21) should be nonnegative, it results  $\tau n + \Delta > n_-$ .

Similarly, by letting  $\zeta' = \kappa'' - \kappa'''$ , we obtain the result

$$\begin{aligned} & \sum_{i=1}^n \rho_{\tau,c}(y_i - \alpha_0 - \delta_\alpha) - \sum_{i=1}^n \rho_{\tau,c}(y_i - \alpha_0) \\ &= -\tau\delta_\alpha n_1 - \tau\delta_\alpha n_2 + \kappa'' + (1 - \tau)\delta_\alpha n_3 - \kappa''' + (1 - \tau)\delta_\alpha n_4 \\ &= -\tau\delta_\alpha(n_1 + n_2) + (1 - \tau)\delta_\alpha(n_3 + n_4) + \zeta' \\ &= \delta_\alpha[-\tau n_+ + (1 - \tau)n_- + \Delta'] \\ &= \delta_\alpha[(1 - \tau)n + \Delta' - n_+], \end{aligned} \tag{22}$$

where  $\Delta' = \zeta'/\delta_\alpha$  which is also negligible with a sufficiently small  $c$ . Therefore, we obtain  $(1 - \tau)n + \Delta' > n_+$ . Combining with (21) and (22), we have

$$\tau - \frac{\Delta'}{n} < \frac{n_-}{n} < \tau + \frac{\Delta}{n}.$$

By the assumption  $\Delta = O(n)$  and  $\Delta' = O(n)$ , we obtain

$$\frac{n_-}{n} \rightarrow \tau + \Delta'',$$

where  $\Delta''$  is negligible when  $c$  is chosen to be effectively zero relative to the magnitude of the data values.  $\square$