

On split conformal prediction

Theorem (marginal validity of SCP): let $(X_i, Y_i)_{i=1}^{n+1}$ be exchangeable. SCP applied on $(X_i, Y_i)_{i=1}^n$ outputs $\hat{C}_\alpha(\cdot)$ such that:

$$\mathbb{P}(Y_{n+1} \in \hat{C}_\alpha(X_{n+1})) \in [1-\alpha; 1-\alpha + \frac{1}{n+1}],$$

where the upper bound holds if the scores $(S_i)_{i \in [n]} \cup \{S_{n+1}\}$ are a.s. distinct.

♥

Proof: A) To begin, let's write explicitly:

$$\begin{aligned} \mathbb{P}(Y_{n+1} \in \hat{C}_\alpha(X_{n+1})) &= \mathbb{P}(\hat{\mu}(X_{n+1}) - q_{1-\alpha}(S) \leq Y_{n+1} \leq \hat{\mu}(X_{n+1}) + q_{1-\alpha}(S)) \\ &= \mathbb{P}(|Y_{n+1} - \hat{\mu}(X_{n+1})| \leq q_{1-\alpha}(S)) \\ \mathbb{P}(Y_{n+1} \in \hat{C}_\alpha(X_{n+1})) &= \mathbb{P}(S_{n+1} \leq q_{1-\alpha}(S)) \quad (\clubsuit) \end{aligned}$$

B) (\clubsuit) makes us want to use the quantile lemma! But how

do $q_{1-\alpha}(S)$ and $q_{1-\alpha}((S_i)_{i \in [n]}, S_{n+1})$ relate?

Recall that $q_{1-\alpha}(S) = q_{1-\alpha}((S_i)_{i \in [n]}, +\infty)$.

In fact, by a careful analysis of the order statistics,

we have that $\mathbb{P}(S_{n+1} \leq q_{1-\alpha}(S)) = \mathbb{P}(S_{n+1} \leq q_{1-\alpha}((S_i)_{i \in [n]}, S_{n+1}))$.

Indeed: \rightarrow noting that $q_{1-\alpha}((S_i)_{i \in [n]}, S_{n+1}) \leq q_{1-\alpha}(S) = q_{1-\alpha}((S_i)_{i \in [n]}, +\infty)$,

we have $\mathbb{P}(S_{n+1} \leq q_{1-\alpha}((S_i)_{i \in [n]}, S_{n+1})) \subseteq \mathbb{P}(S_{n+1} \leq q_{1-\alpha}(S))$.

\rightarrow to prove the reverse inclusion, remark that if S_{n+1} is such that

$S_{n+1} > q_{1-\alpha}((S_i)_{i \in [n]}, S_{n+1})$, it must hold that

$$q_{1-\alpha}((S_i)_{i \in [n]}, S_{n+1}) = q_{1-\alpha}((S_i)_{i \in [n]}, +\infty) = q_{1-\alpha}(S).$$

$S_{n+1} > S_{(\lceil (1-\alpha)(n+1) \rceil)}$ so replacing it by $+\infty$ has no impact.

C) To conclude, note that by exchangeability of $(X_i, Y_i)_{i=1}^n$, we have that

$(S_i)_{i \in \mathcal{C}_\alpha} \cup \{S_{n+1}\}$ are exchangeable (even conditionally on the training data).

for any $j \in \{1, n+1\}$, we can write S_j as $g(X_j, Y_j)$, with g a deterministic function conditional on the training data (or with a remaining randomness independent of $(X_i, Y_i)_{i \in \mathcal{C}_\alpha} \cup (X_{n+1}, Y_{n+1})$).

Hence, we conclude using the quantile lemma on the scores:

$$\begin{aligned} \mathbb{P}(Y_{n+1} \in \hat{\mathcal{C}}_\alpha(X_{n+1})) &= \mathbb{P}(S_{n+1} \leq q_{1-\alpha}((S_i)_{i \in \mathcal{C}_\alpha}, S_{n+1})) \\ &\in [1-\alpha, 1-\alpha + \frac{1}{n_{\mathcal{C}_\alpha}+1}] \end{aligned}$$

with the upper bound when $(S_i)_{i \in \mathcal{C}_\alpha} \cup \{S_{n+1}\}$ are a.s. distincts.

□

Lemma (CQR): $\mathbb{P}(Y_{n+1} \notin \hat{\mathcal{C}}_\alpha(X_{n+1})) = \mathbb{P}(Y_{n+1} < \hat{Q}_{R, \text{lower}}(X_{n+1}) - q_{1-\alpha}(S)$
or $Y_{n+1} > \hat{Q}_{R, \text{upper}}(X_{n+1}) + q_{1-\alpha}(S))$
 $= \mathbb{P}(\hat{Q}_{R, \text{lower}}(X_{n+1}) - Y_{n+1} > q_{1-\alpha}(S)$
or $Y_{n+1} - \hat{Q}_{R, \text{upper}}(X_{n+1}) > q_{1-\alpha}(S))$
 $= \mathbb{P}(\max(\hat{Q}_{R, \text{lower}}(X_{n+1}) - Y_{n+1},$
 $Y_{n+1} - \hat{Q}_{R, \text{upper}}(X_{n+1}))$
 $> q_{1-\alpha}(S))$

$$\mathbb{P}(Y_{n+1} \notin \hat{\mathcal{C}}_\alpha(X_{n+1})) = \mathbb{P}(S_{n+1} > q_{1-\alpha}(S))$$

$$\Leftrightarrow \mathbb{P}(Y_{n+1} \in \hat{\mathcal{C}}_\alpha(X_{n+1})) = \mathbb{P}(S_{n+1} \leq q_{1-\alpha}(S))$$

