

S1 Algorithm. Pseudo-code of ToPs/R

Off-line Stage 0: Dividing the dataset (D)

Input: Entire dataset D

Divide D into disjoint training set (S), the first validation set (V^1), the second validation set (V^2) and testing set (T) which satisfy $D = S \cup V^1 \cup V^2 \cup T$

Output: Training set S , validation sets V^1, V^2 , and testing set T

Off-line Stage 1: Growing the Optimal Tree of Predictors

Input: Feature space X , a set of algorithms \mathcal{A} , training set S , the validation set V^1

First step: Initial tree of predictors = (X, h_X) where $h_X = \arg \min_{A \in \mathcal{A}}$

Recursive step:

Input: Current tree of predictors $(T, \{h_C\})$

for each terminal node $C \in T$ **do**

for a feature i and a threshold τ_i **do**

 Set $C^-(\tau_i) = \{x \in C : x_i < \tau_i\}, C^+(\tau_i) = \{x \in C : x_i \geq \tau_i\}$, Then,

$\{i^*, \tau_i^*, h_{C^-(\tau_i^*)}, h_{C^+(\tau_i^*)}\} = \arg \min \mathcal{L}(h^- \cup h^+, V^1(C^-(\tau_i)) \cup V^1(C^+(\tau_i)))$

 where $h^- \in A(C^-(\tau_i)^\dagger), h^+ \in A(C^+(\tau_i)^\dagger)$

Stopping Criteria: $\mathcal{L}(h_C, V^1(C)) \leq \min \mathcal{L}(h^- \cup h^+, V^1(C^-(\tau_i)) \cup V^1(C^+(\tau_i)))$

Output: Locally optimal tree of predictors $(T, \{h_C\})$

Off-line Stage 2: Weights Optimization on the Path

Input: Locally optimal tree of predictors $(T, \{h_C\})$, the second validation set V^2

for each terminal node \bar{C} and the corresponding path Π from X to \bar{C} **do**

for each weight vector $w = (w_C)$, **do**

 Define $H_w = \sum_{C \in \Pi} w_C h_C$, Then,

$w^*(\Pi) = (w^*(\Pi, \bar{C})) = \arg \min \mathcal{L}(H_w, V^2(\bar{C}))$

Output: Optimized weights $w^*(\Pi)$ for each terminal node \bar{C} and corresponding path Π

On-line Stage: Overall Predictor

Input: Locally optimal tree of predictors $(T, \{h_C\})$, optimized weights $w^*(\Pi)$, and testing set T

 Given a feature vector x

 Find the unique path $\Pi(x)$ from X to terminal node containing x

 Then, $H(x) = \sum_{C \in \Pi(x)} w^*(\Pi, C) h_C(x)$

Output: The final prediction $H(x)$
