
Multivariate Dyadic Regression Trees for Sparse Learning Problems

Appendix

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1 Pseudocode for Greedy Tree Learning Algorithm

Algorithm 1 Tree Growing

Input: $\{\mathbf{x}^i, \mathbf{y}^i\}_{i=1}^n, m, n_{\max}, L, \text{deterministic}$

Build the initial tree T with a single root node r containing all the data points and set $\mathcal{A}(r) \leftarrow \emptyset$

while $\exists t \in \text{term}(T)$ such that $n(t) > n_{\max}$ or $|\mathcal{A}(t)| < d$ **do**

if $|\mathcal{A}(t)| < d$ **then**

for all dimension $k \notin \mathcal{A}(t)$ **do**

calculate $\Delta \hat{R}_1^m(t, k)$

end for

end if

if $n(t) > n_{\max}$ **then**

for all dimension $k \in \mathcal{A}(t)$ **do**

if $\text{sl}(t^{(k)}) \geq 2^{-L+1}$ **then**

calculate $\Delta \hat{R}_2^m(t, k)$

end if

end for

end if

if deterministic then

$(a^*, k^*) = \underset{a \in \{1, 2\}, k \in \{1 \dots d\}}{\text{argmax}} \Delta \hat{R}_a^m(t, k)$

else

Normalize $\Delta \hat{R}$ to 1. Draw the sample (a^*, k^*) from the multinomial(1, $\Delta \hat{R}$)

end if

if $a^* = 1$ **then**

Dyadically split the cell represented by node t perpendicular to dimension k^* and update T

else

$\mathcal{A}(t) \leftarrow \mathcal{A}(t) \cup \{k\}$

end if

end while

Output: Tree T

Note the boolean variable *deterministic* indicates whether the procedure is purely greedy or randomized.

Algorithm 2 Cost Complexity Pruning

Input: Tree T , parameter λ for calculating $\widehat{C}(T)$

$i \leftarrow 1, T_1 \leftarrow T$

while T_i has more than one node **OR** T_i only has the root node r with $\mathcal{A}(r) \neq \emptyset$ **do**

$T^{(1)} \leftarrow \underset{t_L, t_R \in \text{term}(T_i)}{\text{argmin}} \widehat{C}(\text{Tree obtained by merging}$

$t_L, t_R \text{ in } T_i)$
 $T^{(2)} \leftarrow \underset{t \in \text{term}(T_i), k \in \mathcal{A}(t) \setminus \mathcal{A}(\text{par}(t))}{\text{argmin}} \widehat{C}(\text{Tree obtained}$
by removing the dimension k from $\mathcal{A}(t))$

$T_{i+1} \leftarrow \underset{T^{(l)} \in \{1, 2\}}{\text{argmin}} \widehat{C}(T^{(l)})$

$i \leftarrow i + 1$

end while

$i^* \leftarrow \underset{i}{\text{argmin}} \widehat{C}(T_i)$

Output: Optimal Tree T_{i^*}
