TREEES

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Editor:

Abstract

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Keywords: TREEES

1. Introduction

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2. Bayesian Optimization and Bandit-Based Algorithms

2.1 Bayesian Optimization

2.2 SuccessiveHalving and Hyperband

3. A Trio of Tree Algorithms

3.1 SequentialHalving with Decision Tree inputs

3.2 SequentialTree

3.2.1 Algorithm

Algorithm 1 SequentialTree

procedure SequentialTree(Box constrained space $\mathcal{X} \subset \mathbb{R}^d$, budget T, η, m)
  Assign $\mathcal{P} = \{\mathcal{X}\}$ and `n_nodes` $= m$
  for $r = 1 \ldots \lceil \log_\eta(m) \rceil$ **do**
    Assign the number of pulls per element of $\mathcal{P}$, $n_r = \left\lfloor \frac{T}{|\mathcal{P}| \lceil \log_\eta(m) \rceil} \right\rfloor$
    Assign $\mathcal{A}_r = \emptyset$ and $\hat{B}_r = \emptyset$
    for $p \in \mathcal{P}$ **do**
      Remove p from $\mathcal{P}$
      Sample $\{x_{p1}, \ldots, x_{pn_r}\}$ independently and uniformly over p
      Let $\{y_{p1}, \ldots, y_{pn_r}\}$ be the result of querying the function at these points
      Train a decision tree with `n_nodes` nodes, $t_p = \text{DecisionTree}(y_p \sim X_p)$
      Add the `n_nodes` elements of the partition of p defined by t_p to $\mathcal{A}_r$
      Add the prediction from t_p for each element to $\hat{B}_r$.
    end for
    if $|\mathcal{P}| > \eta^2$ **then**
      Set $\mathcal{P}$ to be the elements of $\mathcal{A}_r$ with predictions in the top $\frac{|\mathcal{P}|}{\eta^2}$ of $\hat{B}_r$
    else
      Let $\hat{p}$ be the element of $\mathcal{P}$ with the best prediction
      return MidPoint($\hat{p}$)
    end if
    `n_nodes` $= \eta$
  end for
end procedure

3.3 PartitionTree

3.3.1 Algorithm

Algorithm 2 PartitionTree

procedure PartitionTree(Box constrained space $\mathcal{X} \subset \mathbb{R}^d$, budget T, η, R, k)
  Assign $\mathcal{P} = \{\mathcal{X}\}$, and $m = \eta^2$
  for $r = 1, \ldots, R$ **do**
    The number of pulls per element of $\mathcal{P}$ $n_r = \left\lfloor \frac{T}{|\mathcal{P}|R} \right\rfloor$
    Assign $\mathcal{A}_r = \emptyset$ and $\hat{B}_r = \emptyset$
    for $p \in \mathcal{P}$ **do**
      Remove p from $\mathcal{P}$
      Sample $\{x_{p1}, \ldots, x_{pn_r}\}$ independently and uniformly over p
      Let $\{y_{p1}, \ldots, y_{pn_r}\}$ be the result of querying the function at these points
      Train a decision tree with m nodes, $t_p = \text{DecisionTree}(y_p \sim X_p)$
      Train a random forest with k trees and m nodes per tree
      $rf_p = \text{RandomForest}(y_p \sim X_p)$
      Add the m elements of the partition of p defined by t_p to $\mathcal{A}_r$
      Add the prediction from rf_p for the mid point of each element to $\hat{B}_r$.
    end for
    Set $\mathcal{P}$ to be the elements of $\mathcal{A}_r$ with predictions in the top $\frac{|\mathcal{P}|}{\eta}$ of $\hat{B}_r$
    Let $\hat{p}$ be the element of $\mathcal{P}$ with the best prediction
    $m = \eta$
  end for
  return MidPoint($\hat{p}$)
end procedure

4. Empirical Evaluation

Algorithm	Branin		Hartmann 3D		Hartmann 6D	
	$\sigma = \frac{1}{2}$	$\sigma = 5$	$\sigma = \frac{1}{2}$	$\sigma = 5$	$\sigma = \frac{1}{2}$	$\sigma = 5$
Bayesian Optimization	-1.65	-0.05	-0.19	-0.06	0.02	-
Hyperband	-0.75	-0.56	-0.57	-0.45	-0.14	-0.18
SequentialHalving	-0.83	-0.65	-0.62	-0.54	-0.12	-0.18
PartitionTree	-0.19	-0.31	-0.12	-0.16	-0.02	-0.03
SequentialTree	-0.28	-0.38	-0.29	-0.48	-0.08	-0.10

Table 1: Empirical Rates

5. Conclusion

Acknowledgments

We would like to acknowledge

Appendix A.