Distributed Safe Bayesian Optimization

A thesis submitted
in partial fulfillment for the award of the degree of

Master of Technology

in

Machine Learning and Computing

by

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Certificate

This is to certify that the thesis titled ***Distributed Safe Bayesian Optimization*** submitted by **Shivaprasad Nadagoudr**, to the Indian Institute of Space Science and Technology, Thiruvananthapuram, in partial fulfillment for the award of the degree of **Master of Technology** in **Machine Learning and Computing** is a bona fide record of the original work carried out by him/her under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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Date: January 2021

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I declare that this thesis titled ***Distributed Safe Bayesian Optimization*** submitted in partial fulfillment for the award of the degree of **Master of Technology** in **Machine Learning and Computing** is a record of the original work carried out by me under the supervision of **Dr. Vineeth B. S.**, and has not formed the basis for the award of any degree, diploma, associateship, fellowship, or other titles in this or any other Institution or University of higher learning. In keeping with the ethical practice in reporting scientific information, due acknowledgments have been made wherever the findings of others have been cited.

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This thesis is dedicated to …

Acknowledgements

I acknowledge …

Shivaprasad Nadagoudr

Abstract

Abstract here.

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Abbreviations

GNU	GNU's Not Unix
EMACS	Editor MACroS

Nomenclature

m	Mass of the object
c	Velocity of light

Chapter 1

Introduction

1.1 The Explore-Exploit Tradeoff

The real-world decision-making processes has a feature that presents uncertainity in the outcome of future decision. So it is difficult for agent(decision-maker), due to uncertainity in the result of a given action, to choose the best next action. Most of the real-world tasks aiming at maximising cumulative outcomes require to make many sequential decisions.
Successful completion of such a task necessitates a basic tension: an decision-maker (agent) must constantly choose between exploiting all known good possibilities and researching unknown but potentially better options. This conflict is known as the explore-exploit tradeoff, and it's at the basis of improving decision-making.
The explore-exploit tradeoff can be observed in a variety of natural and artificial systems. Foraging animals in the natural world strive to consume as much food as possible while also seeking out the most rewarding foraging areas [1].

1.2 Multi-Armed Bandit Problem

The Multi-armed Bandit (MAB) problem is a classic mathematical description of the explore-exploit tradeoff [2]. A decision-maker(agent) is faced with a sequential series of decisions in the MAB problem. Each choice requires the decision-maker(agent) to pick between two or more options, often known as arms, each of which has a probability distribution associated with it that models the reward. The decision-maker receives a noisy reward chosen from the related probability distribution after selecting an option. The goal of the decision-maker is to maximise their expected cumulative reward, which is comparable to selecting the option with the highest mean as often as possible.

Algorithm 1.1: Distributed SafeOpt

Input: Objective function f, GP prior(μ, k), Parameter search-space S, Number of parameters d, Number of subspaces per parameter n, Safe seed set S_0, Safety threshold h

foreach $parameter$ ***in*** S **do**
  divide $parameter$ into n subspaces.

Take all combinations of subspaces to form $hyperspaces$.
`/*` n^d `hyperspaces are possible. */`
currentSafeHyperspace = $hyperspace : allHyperspaces | S_0 \in hyperspace$
Deploy optimization process for whole search-space into a single node.

Algorithm 1.2: Deploy Hyperspace

Input: f, GP(μ, k), S, S_0, h, $currentSafeHyperspace$, $allHyperspaces$

Initialize $SafeOpt$ with safe seed points S_0.
if *currentSafeHyperspace* is *leafHyperspace* **then**
  for $i = 1 : 10$ **do**
    run $SafeOpt$ algorithm
  return

for $i = 1 : 10$ **do**
  samplePoint=$SafeOpt$.optimize()
  funcValue=f(samplePoint)
  newSafeHyperspace = hyperspace : allHyperspaces | samplePoint $\in$ hyperspace
  if *funcValue* $\geq h$ *AND newSafeHyperspace* $\neq$ *currentSafeHyperspace* **then**
    Split the search space between two hyperspaces.
    Deploy the newSafeHyperspace into new node with samplePoint as safe seed.
    Change the search space for currentSafeHyperspace accordingly and continue optimization process in same node.
  else
    add samplePoint and funcValue to $SafeOpt$ model.

Bibliography

[1] T. Keasar, E. Rashkovich, D. Cohen, and A. Shmida, "Bees in two-armed bandit situations: Foraging choices and possible decision mechanisms," *Behavioral Ecology*, vol. 13, pp. 757–765, 11 2002.

[2] H. Robbins, "Some aspects of the sequential design of experiments," *Bulletin of the American Mathematical Society*, vol. 58, pp. 527–535, 1952.

List of Publications

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Appendix A
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A.2 Section 2

Data for Appendix A.2 here

Appendix B

Appendix B Title

B.1 Section 1

Data for Appendix B.1 here

B.2 Section 2

Data for Appendix B.2 here