Exploring the Use of Learning Algorithms for Efficient Performance Profiling

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Find bottleneck in program

Analyzing software production:

- Python HTML parser
- Different components (subcalls):
  start with, append, strip, split, match, find, others

Profiler:

- Signal interrupt => statistical profiler
- Instrumenting code => tracing profiler

Existing methods

Statistical Profiler:

- Missing infrequent events
- Too much for low variance events

Tracing Profiler:

- Overhead
- Instrumentation tool

User target and opportunity

User Target:

- User wants to identify bottleneck
- User doesn’t care too much about short running and low variance components

Idea:

- Measure more for longer running and high variance parts of program
- Fewer time profiling for others

Paikana: choosing function calls to profile

Paikana proposes two ways to choose:

a. A racing algorithm: by statistical result
b. Multi-armed bandits: more standard scenario

A racing algorithm:

- Choose component with minimum running time
- Have enough confidence interval

Multi-armed bandits problem

Problem description: You have **K slot machines**, and each machine provides a **random reward** from a **probability distribution** specific to that machine. The objective is to **maximize** the sum of rewards earned through **a sequence** of lever pulls.

Problem analysis: “exploration” (try new action) v.s. “exploitation” (focus on seemingly highest reward one)

Multi-armed bandits problem (cont’)

Standard solutions:

- Naive: random try for a while then focus on the best
- Thompson sampling: the best in confidence*winrate
- UCB: choose high winrate and low variance

Connection to profiling:

- Exploration: profile subfunctions
- Exploitation: profile more on user interested one
  (longer running time and high variance)

Paikana’s solution

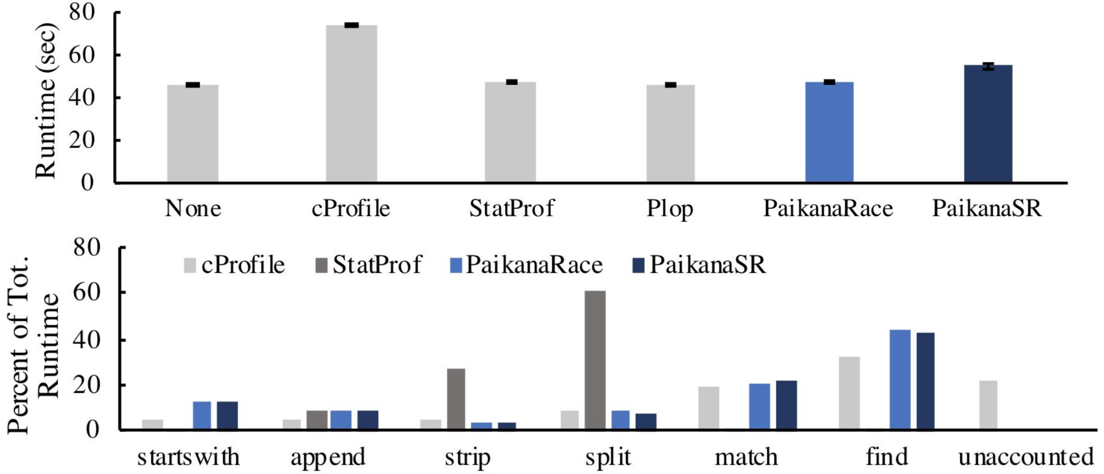
Successive Rejects algorithm from ref [2] (COLT 2010):
“First the algorithm divides the time (i.e., the n rounds) in **K – 1 phases**. At the end of each phase, the algorithm dismisses the arm with **the lowest empirical mean**. During the next phase, it pulls **equally** often each arm which has not been dismissed yet. ”

Parkana profile all candidates equally in each phase, then remove the least valuable one from the candidates.

Result

Shown in two figures:

- Runtime overhead: similar to statistical profiling (low)
- Profiling accuracy: close to runtime profiler (high)



Discussion, my opinion

Strength:

- Combination between program profiling and multi-armed bandits problem
- Insight: users focus on bottleneck components

Weakness:

- Components probability distribution model
- Different testing scenarios, e.g. burst v.s. Stable, or bottleneck migrations (on the fly taking back)

Thanks!

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