Autotuning with Cloud Computing

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Abstract

Test.

1 Introduction

2 Related Work

The Algorithm Selection Problem [15] consists in finding a *mapping* between *problems* and *algorithms* that minimizes the time to solve all instances in a problem set. The algorithms that compose a set can represent different abstractions, such as programs, heuristics, or configurations. The set of problems usually contains instances of a problem. Bougeret *et al.* [5] proved that the Algorithm Selection Problem is NP-complete when calculating static distributions of algorithms in parallel machines. Guo [8] proved the problem is undecidable in the general case.

Rice's conceptual framework formed the foundation of autotuners in various problem domains. In 1997, the PHiPAC system [3] used code generators and search scripts to automatically generate high performance code for matrix multiplication. Since then, systems tackled different domains with a diversity of strategies. Whaley *et al.* [17] introduced the ATLAS project, that optimizes dense matrix multiply routines. The OSKI [16] library provides automatically tuned kernels for sparse matrices. The FFTW [7] library provides tuned C subroutines for computing the Discrete Fourier Transform. In an effort to provide a common representation of multiple parallel programming models, the INSIEME compiler project [12] implements abstractions for OpenMP, MPI and OpenCL, and generates optimized parallel code for heterogeneous multi-core architectures.

Some autotuning systems provide generic tools that enable the implementation of autotuners in various domains. PetaBricks [1] is a language, compiler and autotuner that introduces abstractions, such as the "*either...or*" construct, that enable programmers to define multiple algorithms for the same problem. The ParamILS framework [11] applies stochastic local search methods for algorithm configuration and parameter tuning. The OpenTuner framework [2] provides ensembles of techniques that search spaces of program configurations. Bosboom *et al.* and Eliahu use OpenTuner to implement a domain specific language for data-flow programming [4] and a framework for recursive parallel algorithm optimization [6].

Gupta [9, 10].

2.1 OpenTuner

OpenTuner search spaces are defined by *Configurations*, composed of different *Parameter* types. Each type has restricted bounds, and implements its own manipulation functions, enabling the exploration of the search space. OpenTuner implements ensembles of optimization techniques that perform well in different problem domains.

Results found during the search process are shared between techniques through a common database. OpenTuner uses *meta-techniques* for coordinating the distribution of resources between techniques. An OpenTuner application can implement its own search techniques and meta-techniques.

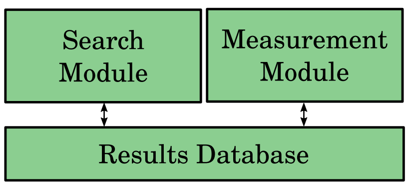


Figure 1: Simplified OpenTuner Architecture.

Figure 1 shows a high-level view OpenTuner's architecture. Measurement and searching are done in separate modules, that share results through the database.

The search module requests measurements by registering configurations to the database. The measurement module reads those configurations and writes back the desired results. Currently, the measurements are performed sequentially.

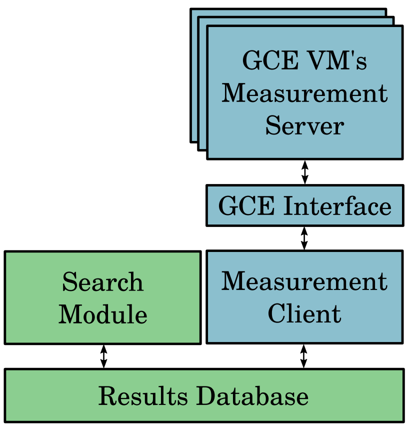
OpenTuner implements optimization techniques such as the Nelder-Mead [14] simplex method and Simulated Annealing [13]. OpenTuner implements a resource sharing mechanism that aims to take advantage of the strengths of each technique. A meta-technique must balance the exploitation of a technique that has produced good results in the past and the exploration of new, and possibly best, techniques.

3 Objectives

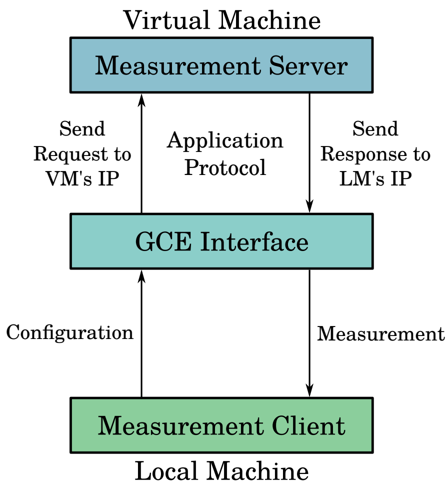
The remaining of this section describes each objective in detail, and reports the current state of the research.

3.1 Measurement Server and Client

It's all about `process_all`. Just checking.



(a)



(b)

3.2 Using the Google Compute Engine

Development on the interface with Google Compute Engine has already started, and the implementations are available[1] under the GNU General Public License.

```python
#!/usr/bin/env python

import socket

TCP_IP = ''
TCP_PORT = 8080
BUFFER_SIZE = 1024

s = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
s.bind((TCP_IP, TCP_PORT))
s.listen(1)

conn, addr = s.accept()

while 1:
    data = conn.recv(BUFFER_SIZE)
    if not data: break
    conn.send(data)
```

Listing 1: A simple echo server in Python.

4 Experiments

5 Research Schedule

6 Conclusion

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[1] All code is hosted at GitHub:
`github.com/phrb/measurement-server`
`github.com/phrb/autotuning-gce`

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