Program Autotuning with
Cloud Computing and OpenTuner

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Abstract. *The OpenTuner framework provides domain-agnostic tools for the implementation of autotuners. The framework sequentially evaluates program configurations exploring search spaces that are commonly very large. Although the autotuner is able to find incrementally better solutions quickly, finding good configurations typically takes a very long time. This sequential search takes even longer to find optimizations for programs with considerable execution times.*

This paper proposes a methodology and a communication protocol for the distributed execution of autotuners implemented in the OpenTuner framework. It presents an extension to the OpenTuner measurement driver that distributes and parallelizes the measurement process using cloud computing resources from the Google Compute Engine (GCE). We compare the performance of our implementation to the unmodified framework using an application benchmark. We offer insight into the problem domains that benefit from this approach.

> *Pedro: A very short summary of the results will be provided in the abstract, as well as a brief discussion of the result normalization research question.*

1. Introduction

> Disclaimer: This is a draft of the paper. The results and implementations are not final or completed. Future versions will improve the presentation and present results and conclusions. The maximum page count for SBRC is 14 pages, and this document is 12 pages long.

The program autotuning problem fits in the framework of the Algorithm Selection Problem, introduced by Rice in 1976 [1]. The objective of an autotuner is to select the best algorithm, or algorithm configuration, for each instance of a problem. Algorithms or configurations are selected according to performance metrics such as the time to solve the problem instance, the accuracy of the solution and the energy consumed. The set of all possible algorithms and configurations that solve a problem defines a *search space*. Various optimization techniques search this space, guided by the performance metrics, for the algorithm or configuration that best solve the problem.

Autotuners can specialize in domains such as matrix multiplication [2], dense [3] or sparse [4] matrix linear algebra, and parallel programming [5]. Other autotuning frameworks provide more general tools for the representation and search of program configurations, enabling the implementation of autotuners for different problem domains [6, 7].

The OpenTuner framework [6] provides tools for the implementation of autotuners for various problem domains. It implements different search techniques that explore the

same search space for program optimizations. Although support for parallel compilation is provided in the framework the empirical exploration of the search space, that is, running and measuring program execution time, is done sequentially.

The main contribution of this paper is the implementation of an OpenTuner extension that distributes and parallelizes the exploration of the optimization space by combining results obtained from virtual machines in a cloud computing environment. A local machine (LM) runs the main OpenTuner application and several virtual machines (VM) run measurement modules that provide results when requested, performing a more efficient exploration of the search space.

The interactions between the local and virtual machines follows the client-server model. The local machine runs a measurement client that requests results from various measurement servers running in virtual machines hosted at the Google Compute Engine (GCE). We compare the performance of our extension with the unmodified framework in a diverse benchmark of applications, identifying the problem domains that benefit from this cloud-based approach.

The rest of the paper is organized as follows. Section 2 discusses related work. Section 3 discusses the architecture of the OpenTuner framework. Section 4 presents the architecture of the measurement driver extension, the GCE interface and the application protocol that mediates the interactions between the *MeasurementClient* and *MeasurementServer*s. Section 5 discusses the result normalization strategies. Section 6 describes the experiments performed and the applications used in the benchmark. Section 7 discusses the results. Section 8 concludes.

2. Related Work

Rice's conceptual framework [1] formed the foundation of autotuners in various problem domains. In 1997, the PHiPAC system [2] 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.* [3] introduced the ATLAS project, that optimizes dense matrix multiply routines. The OSKI [4] library provides automatically tuned kernels for sparse matrices. The FFTW [8] 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 [5] 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 [9] 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 [7] applies stochastic local search methods for algorithm configuration and parameter tuning. The OpenTuner framework [6] 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 [10] and a framework for recursive parallel algorithm optimization [11].

In a progression of papers [12, 13, 14], Gupta *et al.* provide experimental evaluations of the application of cloud computing to high performance computing, describing

which kind of applications has the greatest potential to benefit from cloud computing. Their work highlights small and medium scale projects as the main beneficiaries of cloud computing resources.

> Pedro: Provide a better discussion of Gupta et al.'s results.

> Pedro: Justify the choice of OpenTuner as the modified system, by saying it is a domain-agnostic tool that has, to the best of our knowledge, no equivalent in scope.

3. OpenTuner

OpenTuner search spaces are defined by *Configuration*s, that are composed of *Parameter*s of various types. Each type has restricted bounds and manipulation functions that enable the exploration of the search space. OpenTuner implements ensembles of optimization techniques that perform well in different problem domains. The framework uses *meta-techniques* to coordinate the distribution of resources between techniques. Results found during search are shared through a database. An OpenTuner application can implement its own search techniques and meta-techniques, making the ensemble more robust. The source code is available[1] under the MIT License.
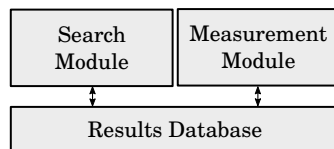

Figure 1. Simplified OpenTuner Architecture.

Figure 1 shows a high-level view of OpenTuner's architecture. Measurement and searching are done in separate modules, whose main classes are called *drivers*. The search driver requests measurements by registering configurations to the database. The measurement driver reads those configurations and writes back the desired results. Currently, the measurements are performed sequentially.

OpenTuner implements optimization techniques such as the Nelder-Mead [15] simplex method and Simulated Annealing [16]. A resource sharing mechanism, called *meta-technique*, aims to take advantage of the strengths of each technique by balancing the exploitation of a technique that has produced good results in the past and the exploration of unused and possibly better ones.

> Pedro: Compare sequential and parallel tuning. Describe when OpenTuner uses threads to compile target programs.

4. Implementation Details

The implementation follows the client-server model, distributing measurements of program configurations between a group of virtual machines running *MeasurementServer*s in the GCE. The servers waits for measurement requests from a client, and maintain copies of the program to be autotuned and the user-defined function that measures configurations.

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[1]Hosted at GitHub: `github.com/jansel/opentuner`

An interface was also implemented to encapsulate the communication from the client enabling a considerably lower implementation effort for the client. Figure 4 show a rough estimate of the implementation effort for the three components of the implementation.

The machine running the OpenTuner autotuner runs a *MeasurementClient*, an extension of the native *MeasurementDriver*, that instead of compiling and running result requests locally, uses the GCE interface to route requests to virtual machines and them saves the results to the local database.
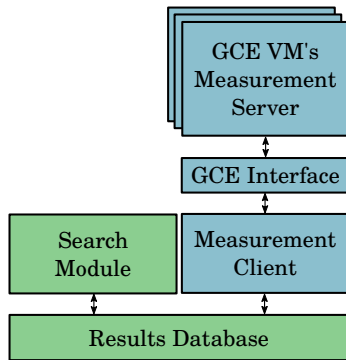

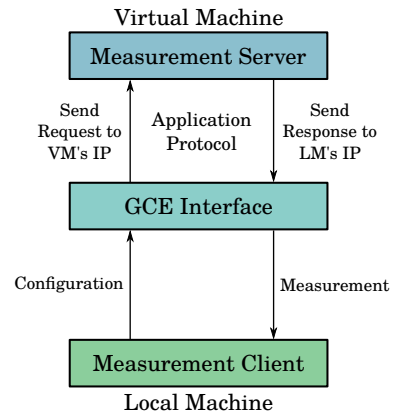**Figure 2. A high-level view of the architecture.**

Figure 3. A lower-level view of the architecture.

Figures 8 and 9 present an overview of the architecture of the extension. Figure 8 presents the architecture of an OpenTuner application running the measurement client and communicating with the measurement servers. Green boxes in the figure represent OpenTuner modules that will not be modified, and blue boxes represent new or modified modules.

Figure 9 shows, on a lower level of abstraction, the interactions between the measurement client and servers. The client requests results from the server through a wrapper of the GCE Python API. The GCE interface also encapsulates the application protocol used in the client-server communication.

The remaining of this section describes the extension implementation in further detail, the GCE interface and the application protocol.

4.1. Measurement Server and Client

OpenTuner controls the execution flow of an application with the `main` function of the *TuningRunMain* class. This function initialises the database and the search and measurement modules. It then calls the `main` function of the search driver, which runs the main loop of the application. The search driver generates configurations to be tested and saves them to the database. It then calls the `process_all` function of the measurement driver and blocks until the function returns.

The `process_all` function calls the `run_desired_results` function, which is able to run compilations in parallel but only sequential measurements. The modified *MeasurementDriver* initialises the GCE interface during its own initialisation. During execution the overridden `process_all` and `run_desired_results` functions route the result
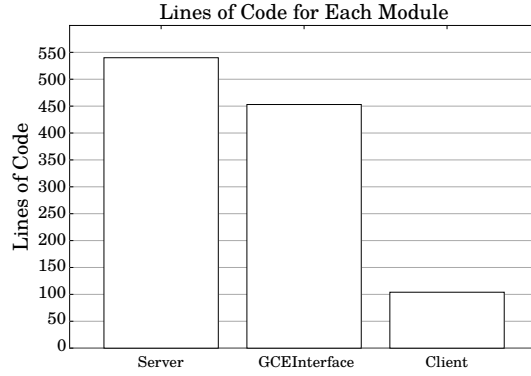
Figure 4. An estimate of the implementation effort, measured in lines of code.

requests to the virtual machines using the *GCEInterface*.

An instance of the *MeasurementServer* runs in every virtual machine. The server is installed after the machine's initialisation and waits for TCP connections from a single client. The application protocol used in communications between the clients and servers is described in Section 4.3.

4.2. GCE Interface

The interactions between the local *MeasurementClient* and the virtual machines' *MeasurementServer*s are mediated by the *GCEInterface*, a wrapper of the GCE Python API. The interface starts and configures virtual machines storing each measurement server's IP.

The interface enables the *MeasurementClient* to request results from the servers without knowledge of the application protocol. Running our client-server implementation in another cloud environment would require a new interface that manages virtual machines in this environment, but no modifications are needed to the server or client.

4.3. Application Protocol

This section describes the text-based application protocol used in the client-server communications mediated by the *GCEInterface*. Note the CLONE message. The user's Open-Tuner application must be a git project available via HTTP. The application will be cloned to the virtual machine by the server and used to obtain the autotuning results requested by the client.

Messages Table 1 shows all the messages in the protocol, a brief description of their meaning and their string format. The client must send a MEASURE message for each configuration that is measured. The server returns a unique ID that is used to retrieve the results when they are ready. This is done by sending a GET message.

Server Responses The server responds to each request with a message template and trailing, message-specific parameters. Responses always start with the correspondent command name and end with a newline character. Each response contains the current

Command	Function	Message
START	Sets the server's status to AVAILABLE	`'START'`
STOP	Sets the server's status to STOPPED	`'STOP'`
STATUS	Requests the server current status	`'STATUS'`
DISCONNECT	Disconnects from the server	`'DISCONNECT'`
SHUTDOWN	Disconnects and shuts the server down	`'SHUTDOWN'`
CLONE	Clones a git repository to the virtual machine	`'CLONE REPO_URL DIST_DIR'`
LOAD	Imports the user's MeasurementInterface into the server	`'LOAD TUNER_PATH INTERFACE_NAME'`
MEASURE	Computes the measurement for a given configuration	`'MEASURE CONFIG INPUT LIMIT'`
GET	Requests a configuration's result	`'GET RESULT_ID'`

Table 1. Server messages.

server status (`SERVER_STATUS`) and error code of the command (`ERROR_STATUS`). The optional argument list (`[ARGS..]`) contains the measurement result, for example, in the case of a successful `GET` response. Figure 5 shows the format of a server response.

```
'COMMAND ERROR_STATUS SERVER_STATUS [ARGS..]  [MESSAGE]'
```

Figure 5. The format of a server response.

Code Availability   The code for the measurement server, client and the interface is available[2] under the GNU General Public License.

5. Result Normalization

Using a cloud environment, an autotuner will typically optimize programs for a machine with a different architecture from the virtual machines. A normalization technique must be devised that enables the results found in the virtual machines to be valid for the local machine. We present four approaches to this problem. The best approach for each problem domain must be experimentally determined, and could be a combination of the approaches described here.

Autotune Performance Models   Another autotuner could be implemented to optimize parameters of a simple performance model, that would associate a configuration's measurement and the virtual machine that produced it with a conversion function that transposes performance results to the target architecture.

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[2]All code is hosted at GitHub:

github.com/phrb/measurement-server

github.com/phrb/gce_interface

github.com/phrb/measurement_client

Ensembles of Virtual Machines   The cloud application could be composed of virtual machines with different architectures. The final performance measurement for a configuration would be built from some combination of the results obtained in these different virtual machines.

Architecture Simulators   The target machine could be modeled by an architecture simulator such as *zsim* [17], a simulator for multi-core architectures available[3] under the GNU General Public License. Using a simulator would solve the normalization problem but introduce other problems, such as the simulator's accuracy and performance.

Autotune in the Cloud   Finally, the normalization problem could be sidestepped, at least in initial stages of research, by running the servers and clients in the cloud using the same kind of virtual machine.

6. Experiments

This section describes the problems that compose the benchmark and the Google Compute Engine's virtual machines and project settings. The performances of the autotuners for each problem in the benchmark were measured in 12 different experimental settings. Each tuning run lasted 15 minutes, used 2, 4 or 8 virtual machines, and was repeated 4 times. We also varied the number of result requests that each virtual machine in a tuning run processed, namely 1, 4, 8 or 16 requests per machine.

6.1. Using the Google Compute Engine

All virtual machines used in the experiments had a single vCPU and 3.75Gb of RAM (Google Compute Engine machine type `n1-standard-1`). All experiments were performed with machines from the `us-central1-f` zone. We built a virtual machine image with the latest stable Debian distribution and all dependencies installed, speeding up the virtual machines' initialization time.

6.2. Travelling Salesperson Problem

The instances of the Travelling Salesperson Problem (TSP) used in the experiments in this paper were obtained from TSPLIB [18]. A TSP solver was implemented as an OpenTuner application. The search space was defined by all the possible permutations, or tours, of cities where the first and last cities are the same. We used two instances, of size 532 and 85900.

7. Results

> Pedro: This section will present and discuss the results, connecting the findings with normalization techniques and problem domains.

7.1. Travelling Salesperson Problem

> Pedro: Here we will discuss the results for the TSP. We will argue that we achieved results very close to a high-end machine using cheap and low-end virtual machines.

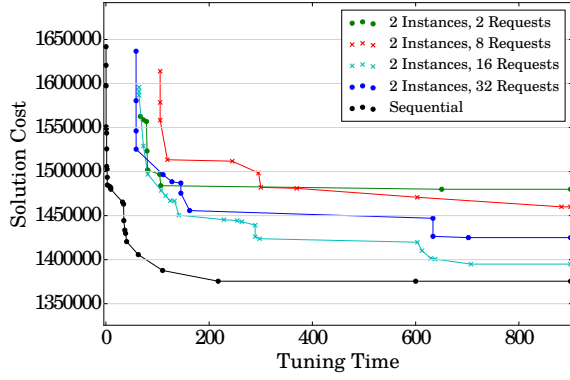[3]Hosted at GitHub: `https://github.com/s5z/zsim`

Figure 6. Measurements using two virtual machine instances, solving a TSP instance of size 532.
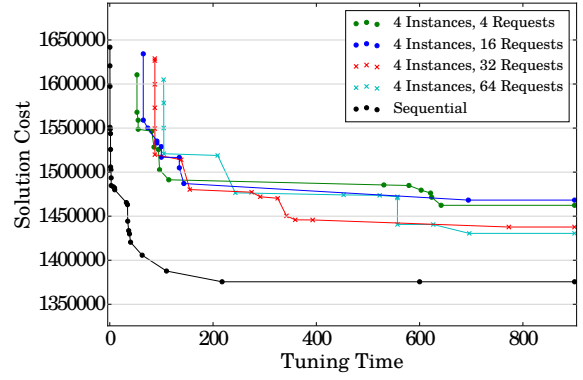

Figure 7. Measurements using four virtual machine instances, solving a TSP instance of size 532.
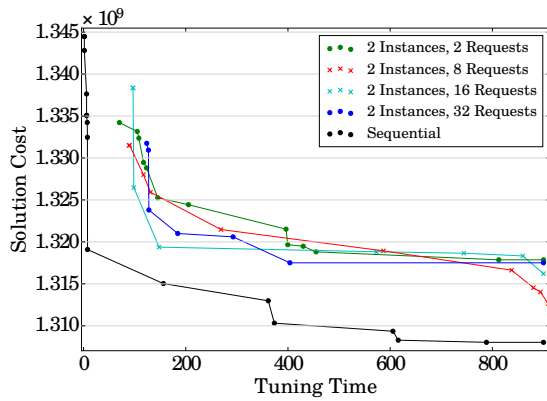

Figure 8. Measurements using two virtual machine instances, solving an instance of size 85900.
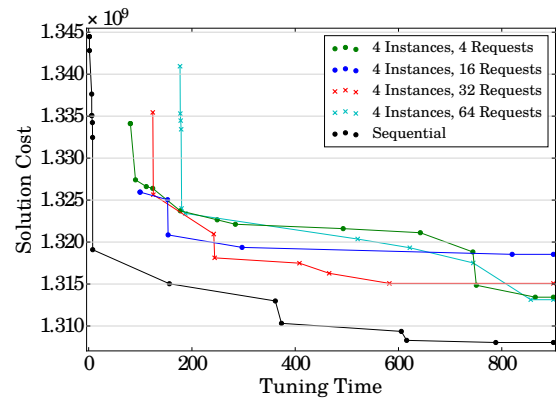

Figure 9. Measurements using four virtual machine instances, solving an instance of size 85900.

8. Conclusion

This paper presented an extension of the OpenTuner autotuning framework enabling it to leverage the cloud computing resources from GCE. We propose four approaches to solve the result normalization problem which would enable transposing the results obtained in virtual machines to a local machine.

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