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Towards Collaborative Performance Tuning of Algorithmic Skeletons

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Abstract

The physical limitations of microprocessor design have forced the industry towards increasingly heterogeneous designs to extract performance. This trend has not been matched with adequate software tools, leading to a growing disparity between the availability of parallelism and the ability for application developers to exploit it.

Algorithmic skeletons simplify parallel programming by providing high-level, reusable patterns of computation. Achieving performant skeleton implementations is a difficult task; skeleton authors must attempt to anticipate and tune for a wide range of architectures and use cases. This results in implementations that target the general case and cannot provide the performance advantages that are gained from tuning low level optimization parameters. Autotuning combined with machine learning offers promising performance benefits in these situations, but the high cost of training and lack of available tools limits the practicality of autotuning for real world programming. We believe that performing autotuning at the level of the skeleton library can overcome these issues.

In this work, we present OmniTune — an extensible and distributed framework for dynamic autotuning of optimization parameters at runtime. OmniTune uses a client-server model with a flexible API to support machine learning enabled autotuning. Training data is shared across a network of cooperating systems, using a collective approach to performance tuning.

We demonstrate the practicality of OmniTune in a case study using the algorithmic skeleton library SkelCL. By automatically tuning the workgroup size of OpenCL Stencil skeleton kernels, we show that that static tuning across a range of GPUs and programs can achieve only 26% of the optimal performance, while OmniTune achieves 92% of this maximum, equating to an average 5.65× speedup. OmniTune achieves this without introducing a significant runtime overhead, and enables portable, cross-device and cross-program tuning.

1. Introduction

General purpose programming with GPUs has been shown to provide huge parallel throughput, but poses a significant programming challenge, requiring application developers to master an unfamiliar programming model (such as provided by CUDA or OpenCL) and architecture (SIMD with a multi-level memory hierarchy). As a result, GPGPU programming is often considered beyond the realm of everyday development. If steps are not taken to increase the accessibility of such parallelism, the gap between potential and utilized performance will continue to widen as hardware core counts increases.

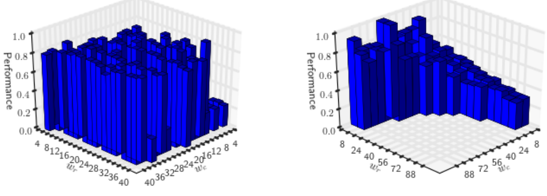
Algorithmic skeletons offer a solution to this this *programmability challenge* by raising the level of abstraction. This simplifies parallel programming, allowing developers to focus on solving problems rather than coordinating parallel resources. Skeleton frameworks provide robust parallel implementations of common patterns of computation which developers parameterise with their application-specific code. This greatly reduces the challenge of parallel programming, allowing users to structure their problem-solving logic sequentially, while offloading the cognitive cost of parallel coordination to the skeleton library author. The rising number of skeleton frameworks supporting graphics hardware illustrates the demand for high level abstractions for GPGPU programming [1, 2]. The challenge is in maintaining portable performance across the breadth of devices in the rapidly developing GPU and heterogeneous architecture landscape.

1.1 The Performance Portability Challenge

There are many factors — or *parameters* — which influence the behavior of parallel programs. For example, setting the number of threads to launch for a particular algorithm. The performance of parallel programs is sensitive to the values of these parameters, and when tuning to maximize performance, one size does not fit all. The suitability of parameter values depends on the program implementation, the target hardware, and the dataset that is operated upon. Iterative compilation and autotuning have been shown to help in these cases by automating the process of tuning parameter values to match individual execution environments [3]. However, there have been few attempts to develop general mechanisms for these techniques, and the time taken to develop ad-hoc autotuning solutions and gather performance data is often prohibitively expensive.

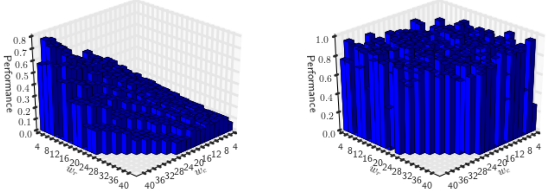
We believe that by embedding autotuning at the skeletal level, it is possible to achieve performance with algorithmic skeletons that is competitive with — and in some cases, exceeds — that of hand tuned parallel implementations which traditionally came at the cost of many man hours of work from expert programmers to develop.

Incorporating autotuning into algorithmic skeleton libraries has two key benefits: first, it minimizes development effort by requiring only a modification to the skeleton implementation rather than to every user program; and second, by targeting a library, it enables a broader and more substantive range of performance data to be gathered than with ad-hoc tuning of individual programs.



(a) (b)

Figure 1: The performance of different workgroup sizes for the same stencil program on two different devices: (a) Intel CPU, (b) NVIDIA GPU. Selecting an appropriate workgroup size depends on the execution device.



(a) (b)

Figure 2: The performance of different workgroup sizes for two different stencil programs on the same execution device. Selecting an appropriate workgroup size depends on the program.

1.2 Contributions

The key contributions of this work are:

- The design and implementation of a generic toolset for autotuning: *OmniTune* is a novel and extensible framework for collaborative autotuning of optimization parameters across the life cycle of programs.
- The integration of OmniTune with an established skeleton library for CPU and multi-GPU parallelism, SkelCL [4]. We extend SkelCL to provide autotuning for the selection of OpenCL workgroup size for Stencil skeletons.
- An empirical evaluation of OmniTune across 7 different architectures, demonstrating that OmniTune achieves 92% of the best possible performance, providing a median speedup of 5.65× over the best possible statically chosen workgroup size.

2. Motivation

In this section we will briefly examine the performance impact of selecting workgroup size for the SkelCL Stencil skeleton. A full explanation of SkelCL and the workgroup size parameter space is given Section 4.

SkelCL uses OpenCL to parallelise skeleton operations across many threads. In OpenCL, multiple threads are grouped into *workgroups*. The shape and size of these groups is known to have a big impact on performance. For the SkelCL stencil skeleton, the selection of workgroup size presents a two dimensional parameter space, consisting of a number of rows and columns ($w_r \times w_c$). Measuring and plotting the runtime of stencil programs using different workgroup sizes allows us to compare the performance of different workgroup sizes for different combinations of architecture and program. Figure 1 shows this performance comparison for a single stencil program on two different devices, demonstrating that a good choice of workgroup size is device dependent. The optimization space of the same stencil benchmark on different devices is radically different: not only does the optimal workgroup size change between devices, but the performance of suboptimal workgroup sizes is also dissimilar. The optimization space of 1a has a grid-like structure, with clear performance advantages of workgroup sizes at multiples of 8 for w_c. A developer specifically targeting this device would learn to select workgroup sizes following this pattern. This domain specific knowledge clearly does not transfer to the device shown in 1b.

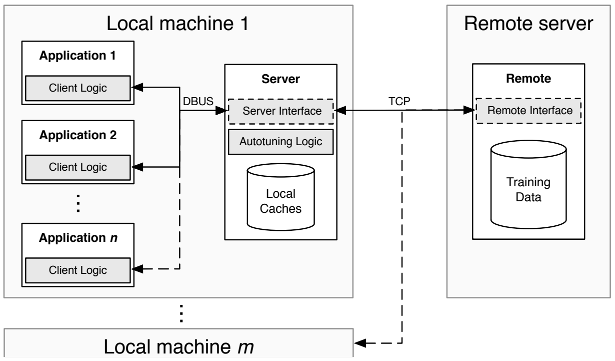


Figure 3: OmniTune system architecture, showing the separate components and the one to many relationship between servers to client applications, and remotes to servers.

In Figure 2, we compare the performance of two different stencil programs on the *same* device, showing that workgroup size choice is also program dependent. In each of these four examples, the optimal workgroup size changes, as does the relative performance of suboptimal parameters. The average speedup of the best over the worst workgroup size is 37.0×, and the best average performance that can be achieved using a single fixed workgroup size is only 63% of the maximum.

SkelCL uses a fixed workgroup size by default. Since both the execution device and the user-provided stencil code are not known until runtime, selection of workgroup size should be made dynamically. To the best of our knowledge, there is currently no such generic system which meets our requirements for lightweight runtime machine learning autotuning with distributed training sets, and as a result, a variety of autotuners have been developed ad-hoc and on a per-case basis.

3. The OmniTune Framework

OmniTune is a novel framework for extensible, distributed autotuning of parameter values at runtime using machine learning. It serves as a generic platform for developing autotuning solutions, aiming to reduce both the engineering time required to target new optimization parameters, and the time to deploy on new systems.

It emphasizes collaborative, online learning of optimization spaces. A client-server architecture with clearly delineated separation of concerns minimizes the code footprint in client applications, enabling quick re-purposing for autotuning targets. OmniTune provides a lightweight interface for communication between each of the components, and aims to strike a balance between offering a fully featured environment for quickly implementing autotuning, while providing enough flexibility to cater to a wide range of use cases. First, we describe the overall structure of OmniTune and the rationale for the design, followed by the interfaces and steps necessary to apply OmniTune.

3.1 System Architecture

Common implementations of autotuning in the literature either embed the autotuning logic within each target application (e.g. [5]), or take a standalone approach in which the autotuner is a program which must be externally invoked by the user to tune a target application (e.g. [6]). Embedding the autotuner within each target application has the advantage of providing "always-on" behavior, but is infeasible for complex systems in which the cost of building machine learning models must be added to each program run. The standalone approach separates the autotuning logic, at the expense of adding one additional step to the build process. The approach taken in OmniTune aims to combine the advantages of both techniques by implementing autotuning *as a service*, in which a standalone autotuning server performs the heavy lifting of managing training data and machine learning models, with a minimal set of lightweight communication logic to be embedded in target applications.

OmniTune is built around a three tier client-server model, shown in Figure 3. The applications which are to be autotuned are the *clients*. These clients communicate with a system-wide *server*, which handles autotuning requests. The server communicates and caches data sourced from a *remote* server, which maintains a global store of all autotuning data. There is a many to one relationship between clients, servers, and remotes, such that a single remote may handle connections to multiple servers, which in turn may accept connections from multiple clients. This design has two primary advantages: the first is that it decouples the autotuning logic from that of the client program, allowing developers to easily repurpose the autotuning framework to target additional optimization parameters without a significant development overhead for the target applications; the second advantage is that this enables collective tuning, in which training data gathered from a range of devices can be accessed and added to by any OmniTune server.

The OmniTune framework is implemented as a set of Python classes which are extended to target specific parameters. The generic implementation of OmniTune's server and remote components consists of 8987 lines of Python and MySQL code. No client logic is provided, since that is use case dependent (See Section 4 for an example implementation for SkelCL). Inter-process communication between client programs and the server uses the D-Bus protocol. D-Bus is cross-platform, and bindings are available for most major programming languages, allowing flexibility for use with a range of clients. Communication between servers and remotes uses TCP/IP (we used an Amazon Web Services database instance for development).

3.2 Autotuning Behavior

The goal of machine learning enabled autotuning is to build models from empirical performance data of past programs to select parameter values for new *unseen* programs. Instead of an iterative process of trial and improvement, parameter values are *predicted*, by building correlations between performance, and *features* (explanatory variables). The data used to build such models is called training data. OmniTune supports autotuning using a separate offline training phase, online training, or a mixture of both. For each autotuning-capable machine, an OmniTune server acts as an intermediary between training data and the client application, and hosts the autotuning logic. On launch, a server requests the latest training data from the remote, which it uses to build the relevant models for performing prediction of optimization parameter values. If additional training data is gathered by the server, this can be uploaded to the remote.

While the data types of the autotuning interface are application-specific (e.g. a binary flag or one or more numeric values), the general pattern is that a client application will request parameter values from an OmniTune server by sending it a set of explanatory variables. The server will then use machine learning models to form a prediction for the optimal parameter values and return these. Crucially, there is a mechanism provided for the client to *refuse* parameter values. This functionality is provided for cases where the predicted parameter values are in some way invalid and do not lead to a valid program.

The server contains a library of machine learning tools to perform parameter prediction, interfacing with the popular datamining software suite Weka[1] using its Java Native Interface. The provided tools include classifiers, regressors, and a selection of meta-learning algorithms.

OmniTune servers may perform additional feature extraction of explanatory variables supplied by incoming client requests. The reason for performing feature extraction on the server as opposed to on the client side is that this allows the results of expensive operations (for example, analyzing source code of target applications) to be cached for use across the lifespan of client applications. The contents of these local caches are periodically and asynchronously synced with the remote to maintain a global store of lookup tables for expensive operations.

3.3 Interfaces

Key design elements of OmniTune are the interfaces exposed by the server and remote components. Figure 4 shows an example communication pattern between the three components of an OmniTune system using these interfaces. In the example, a server first requests training data from the remote. A client application then performs a training phase in which it requests a set of parameters for training, evaluates the performance of the parameters, and then submits a measured value, which the server uses to update the remote. After training, another client program requests a set of parameters for performance, refuses them, and makes a new request.

Client-Server An OmniTune server exposes a public interface over D-Bus with four operations. Client applications invoke these methods to request parameter values, submit new training observations, and refuse suggested parameters:

- Request(x : feature vector) → p : param
  Given explanatory variables x, request the parameter values p which are expected to provide maximum performance.
- RequestTraining(x : feature vector) → p : param
  Given explanatory variables x, allow the server to select parameter values p for evaluating their fitness.

[1] `http://www.cs.waikato.ac.nz/ml/weka/`

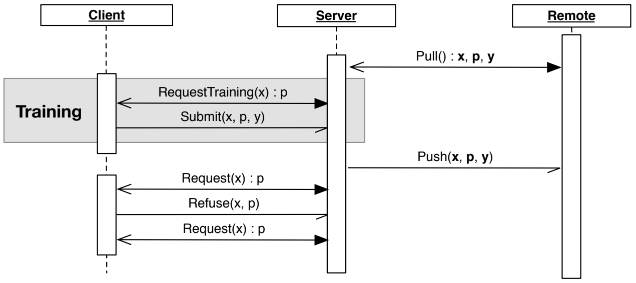


Figure 4: An example communication pattern between OmniTune components, showing an offline training phase.

- Submit(x : feature vector, p : param, y : fitness)
Submit an observed measurement of fitness y for parameter values p, given explanatory variables x.
- Refuse(x : feature vector, p : param)
Refuse parameter values p, given a set of explanatory variables x. Once refused, those parameters are blacklisted and will not be returned by any subsequent calls to Request() or RequestTraining() for the same explanatory variables x.

Server-Remote The role of the remote is to provide bookkeeping of training data for machine learning. Remotes allow shared access to data from multiple servers using a transactional communication pattern, supported by two methods:

- Push($\mathbf{x}$: feature vectors, $\mathbf{p}$: params, $\mathbf{y}$: fitnesses)
Asynchronously submit training data as three lists: explanatory variables $\mathbf{x}$, parameter values $\mathbf{p}$, and observed outcomes $\mathbf{y}$.
- Pull() → ($\mathbf{x}$: feature vectors, $\mathbf{p}$: params, $\mathbf{y}$: fitnesses)
Request training data as three lists: explanatory variables $\mathbf{x}$, parameter values $\mathbf{p}$, and observed outcomes $\mathbf{y}$.

3.4 Extensibility

To extend OmniTune to target an optimization parameter, a developer extends the server class to implement response handlers for the four public interface operations, and then inserts client code into the target application to call these operations. The implementation of these response handlers and invoking client code determines the type of autotuning methods supported. Figure 5 shows the flow diagram for an example OmniTune implementation. The call to RequestTraining() is matched with a response call of Submit(), showing the client recording a training observation. In the next Section, we will detail the steps required to apply OmniTune to SkelCL.

4. Integration of OmniTune with SkelCL

In this section we demonstrate the practicality of OmniTune by integrating the framework into an established algorithmic skeleton library. Introduced in [4], SkelCL allows users to easily harness the power of GPUs and CPUs for data parallel computing, offering a set of OpenCL implementations of data parallel skeletons in an object oriented C++ library.

The goal of SkelCL is to enable the transition towards higher-level programming of GPUs, without requiring users to be intimately knowledgeable of the concepts unique to OpenCL programming, such as the memory or execution model. SkelCL has been shown to reduce programming effort for developing real applications through the use of robust pattern implementations and automated memory management. Skeletons are parameterised with user functions which are compiled into OpenCL kernels for execution on device hardware. SkelCL supports operations on one or two dimensional arrays of data, with the Vector and Matrix container types transparently handling lazy transfers between host and device memory, and supporting partitioning for multi-GPU execution. SkelCL is freely available and distributed under dual GPL and academic licenses[2].

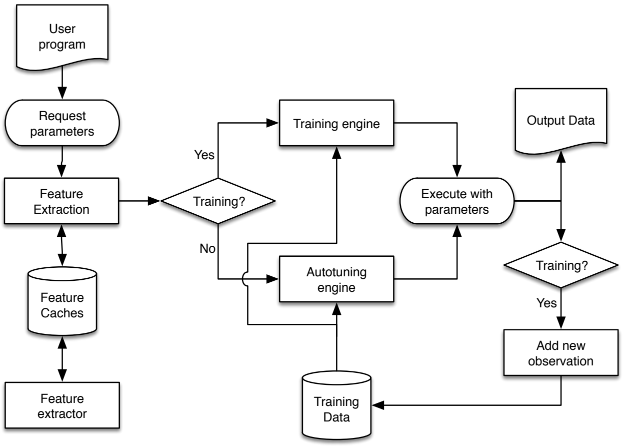


Figure 5: Predicting parameter values and collecting training data with OmniTune.

4.1 The Stencil Skeleton

Stencils are patterns of computation which operate on uniform grids of data, where the value of each grid element (cell) is updated based on its current value and the value of one or more neighboring elements, called the *border region*. Figure 6 shows the use of a stencil to apply a Gaussian blur to an image. SkelCL provides a 2D stencil skeleton which allows users to provide a function which updates a cell's value, while SkelCL orchestrates the parallel execution of this function across all cells [7].

The border region is described by a *stencil shape*, which defines an $i \times j$ rectangular region around each cell which is used to update the cell value. Stencil shapes may be asymmetrical, and are defined in terms of the number of cells in the border region to the north, east, south, and west of each cell. Given a function f, a stencil shape S, and an $n \times m$ matrix with elements x_{ij}:

$$\text{Stencil}\left(f, S, \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix}\right) \to \begin{bmatrix} z_{11} & \cdots & z_{1m} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nm} \end{bmatrix} \quad (1)$$

where:

$$z_{ij} = f\left(\begin{bmatrix} x_{i-S_n,j-S_w} & \cdots & x_{i-S_n,j+S_e} \\ \vdots & \ddots & \vdots \\ x_{i+S_s,j-S_w} & \cdots & x_{i+S_s,j+S_e} \end{bmatrix}\right) \quad (2)$$

For border region elements outside the bounds of the matrix, values are substituted from either a predefined padding value, or the value of the nearest element within the matrix, depending on user preference.

[2] http://skelcl.uni-muenster.de

A popular usage of Stencil codes is for iterative problem solving, whereby a stencil operation is repeated over a range of discrete time steps $0 \leq t \leq t_{max}$, and $t \in \mathbb{N}$. An iterative stencil operation g accepts a customizing function f, a Stencil shape S, and a matrix M with initial values M_{init}. The value of an iterative stencil can be defined recursively as:

$$g(f, S, M, t) = \begin{cases} \text{Stencil}\left(f, S, g(f, S, M, t-1)\right), & \text{if } t \geq 1 \\ M_{init}, & \text{otherwise} \end{cases} \tag{3}$$

Examples of iterative stencils include cellular automata and partial differential equation solvers.

In the implementation of the SkelCL stencil skeleton, each element in the matrix is mapped to a unique thread (known as a *work item* in OpenCL) which applies the user-specified function. The work items are then divided into *workgroups* for execution on the target hardware. Each work-item reads the value of its corresponding matrix element and the surrounding elements defined by the border region. Since the border regions of neighboring elements overlap, the value of all elements within a workgroup are copied into a *tile*, allocated as a contiguous region of the fast, but small local memory. As local memory access times are much faster than that of global device memory, this greatly reduces the latency of the border region memory accesses performed by each work item. Changing the size of workgroups thus affects the amount of local memory required for each workgroup, and in turn affects the number of workgroups which may be simultaneously active on the device. While the user defines the data size and type, the shape of the border region, and the function being applied to each element, it is the responsibility of the SkelCL stencil implementation to select an appropriate workgroup size to use.

4.2 Optimization Parameters

SkelCL stencil kernels are parameterised by a workgroup size w, which consists of two integer values to denote the number of rows and columns in a workgroup. The space of optimization parameter values is subject to hard constraints, and these constraints cannot conveniently be statically determined. Contributing factors are architectural limitations, kernel constraints, and parameters which are refused for other reasons. Each OpenCL device imposes a maximum workgroup size which can be statically checked. These are defined by architectural limitations of how code is mapped to the underlying execution hardware. At runtime, once an OpenCL program has been compiled to a kernel, users can query the maximum workgroup size supported by that particular kernel dynamically. This value cannot easily be obtained statically as there is no mechanism to determine the maximum workgroup size for a given source code and device without first compiling it, which in OpenCL does not occur until runtime.

Factors which affect a kernel's maximum workgroup size include the number of registers required for a kernel, and the available number of SIMD execution units for each type of instructions in a kernel. In addition to satisfying the constraints of the device and kernel, not all points in the workgroup size optimization space are guaranteed to provide working programs. A *refused parameter* is a workgroup size which satisfies the kernel and architectural constraints, yet causes a `CL_OUT_OF_RESOURCES` error to be thrown when the kernel is enqueued. Note that in many OpenCL implementations, this error type acts as a generic placeholder and may not necessarily indicate that the underlying cause of the error was due to finite resources constraints. We define a *legal* workgroup size as one which, for a given *scenario* s (a combination of program, device, and dataset), satisfies the architectural and kernel constraints, and is not refused. The subset of all possible workgroup sizes $W_{legal}(s) \subset W$ that are legal for a given scenario s is then:

$$W_{legal}(s) = \{w | w \in W, w < W_{\max}(s)\} - W_{refused}(s) \tag{4}$$

Where $W_{\max}(s)$ can be determined at runtime prior to the kernels execution, but the set $W_{refused}(s)$ can only be determined experimentally.

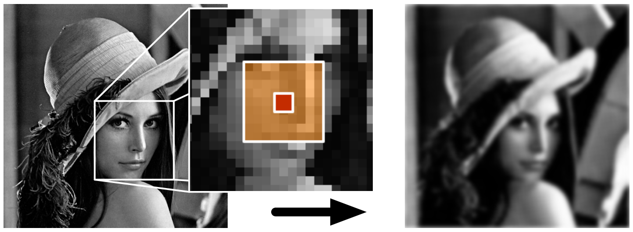


Figure 6: Application of a Gaussian blur stencil operation to an image, with a border region of radius 1. In a Gaussian blur, pixel values are interpolated with neighboring pixels, producing a smoothed effect.

The *oracle* workgroup size $\Omega(s) \in W_{legal}(s)$ of a scenario s is the w value which provides the lowest mean runtime. The relative performance $p(s, w)$ of a particular workgroup against the maximum available performance for that scenario, within the range $0 \leq p(s, w) \leq 1$, is the ratio of the runtime of a program with workgroup size w over the oracle workgroup size $\Omega(s)$. For a given workgroup size, the average performance $\bar{p}(w)$ across a set of scenarios S can be found using the geometric mean of performance relative to the oracle:

$$\bar{p}(w) = \left(\prod_{s \in S} p(s, w) \right)^{1/|S|} \tag{5}$$

4.3 Machine Learning

The optimization space presented by the workgroup size of OpenCL kernels is large, complex, and non-linear. The challenge is to design a system which, given a set of prior observations of the empirical performance of stencil codes with different workgroup sizes, predict workgroup sizes for *unseen* stencils which will maximize the performance. Successfully applying machine learning requires plentiful training data, the careful selection of explanatory variables, and appropriate machine learning methods. For the purpose of this work we use a *classification* approach, in which a classifier automatically correlates patterns between explanatory variables and the workgroup sizes which provide optimal performance. The classifier used is the popular J48 Decision Tree [8], chosen due to its low classification cost and ability to efficiently handle large dimensionality training data.

For each scenario, a total of 102 explanatory variables are extracted to capture information about the device, program, and dataset. Device variables encode the device type (e.g. CPU or GPU, integrated or external, connection bus), properties about the host (e.g. system memory, maximum clock frequency), and numerous properties about the execution device (e.g. number of compute units, local memory size, global caches). Program variables include instruction densities for each instruction type, the total number of basic blocks, and the total instruction count. They are extracted using static instruction count passes over an LLVM IR compiled version of the user stencil implementation. Compilation to bitcode is a relatively expensive task, so lookup tables are used to cache repeated uses of the same stencil codes, identified by a checksum of the source code. Dataset variables include the data types (input and output), and dimensions of the input matrix and stencil region.

To collect training data, we run multiple iterations of a stencil program to enumerate the workgroup size optimization space, and use the OpenCL's Profiling API to record stencil kernel execution times in the client application, which are then submitted to the OmniTune server. The REQUEST-TRAINING(x) server interface returns a workgroup size with a randomly selected even number of rows and columns that obeys the maximum size constraints.

A parameterised template substitution engine is used to generate synthetic stencil applications for gathering performance data. Stencils templates are parameterised with a border region size and *complexity*, a simple metric to broadly dictate the number of operations in a given stencil code.

Once the performance of different workgroup sizes for a scenario is assessed, the set of explanatory variables describing the scenario is paired with the oracle workgroup size. This process is repeated for multiple scenarios to create training data. A classifier learns from this training data to make predictions for new sets of explanatory variables, by predicting a workgroup size from the set of oracle workgroup sizes of the training data.

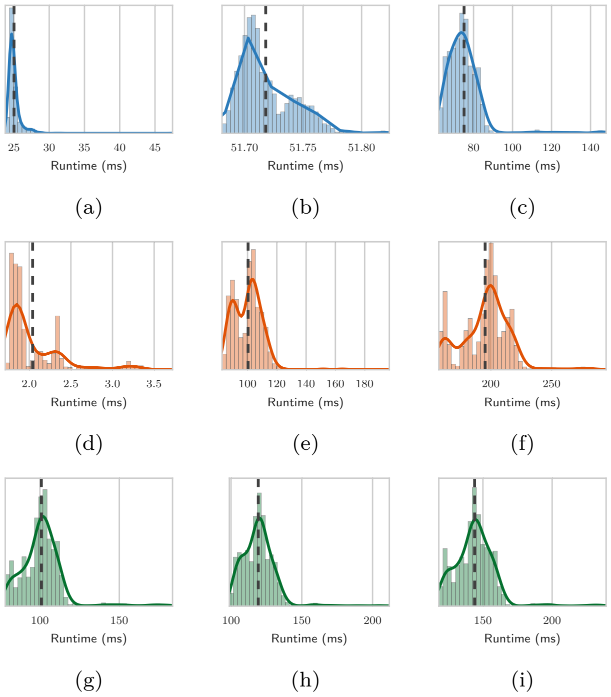
This approach presents the problem that after training, there is no guarantee that the set of workgroup sizes which may be predicted is within the set of legal workgroup sizes for future scenarios. This may result in a classifier predicting a workgroup size which is not legal for a scenario, $w \notin W_{legal}(s)$, either because it exceeds $W_{\max}(s)$, or because the parameter is refused. If this occurs, a *nearest neighbor* approach is used to select the workgroup size w which is expected to be legal and has the lowest Euclidian distance to the predicted value c. This is achieved by comparing row (r) and column (c) indices:

$$w = \underset{w \in W_{legal(s)}}{\arg\min} \sqrt{(c_r - w_r)^2 + (c_c - w_c)^2} \tag{6}$$

This process of selecting alternative parameters will iterate until a legal parameter is found.

4.4 Implementation

The OmniTune framework consists of 8987 lines of Python and MySQL code. A further 976 lines are required for the SkelCL frontend to implement the server response handlers and database backend. By design, the client-server model minimizes the impact of number of modifications that are required to enable autotuning in client applications. The only modification required to SkelCL is to replace the hard-coded values for workgroup size with a subroutine to request a workgroup size from the OmniTune server over a D-Bus connection. To use the system, a user must download a copy of SkelCL modified with the OmniTune functionality, and start a local OmniTune server instance. A configuration file is used to determine the domain address and authentication details of the remote server. On first launch, the OmniTune server will fetch the latest training data from the remote.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Figure 7: Distribution of runtime samples for test cases from three devices. Each plot contains a 35-bin histogram of 1000 samples, and a fitted kernel density estimate with bandwidth 0.3. The sample mean is shown as a vertical dashed line. The top row are from the Intel i5-4570, the second row from the Nvidia GTX 590, and the third row from the AMD Tahiti 7970. In some of the plots, the distribution of runtimes is bi- or multi-modal, and skewed to the lower end of the runtimes range.

5. Experimental Setup

This section describes an exhaustive enumeration of the workgroup size optimization space for 429 combinations of architecture, program, and dataset. It contains the methodology used to collect empirical performance data on which to base performance comparisons of different workgroup sizes, and the steps necessary to obtain repeatable results.

A full enumeration of the workgroup size optimization spaces was performed across synthetically generated benchmarks and four reference stencil benchmarks: Canny Edge Detection, Conway's Game of Life, Heat Equation, and Gaussian Blur [4]. Performance data was collected from 7 experimental platforms, comprising 4 GPU devices: AMD Tahiti 7970, Nvidia GTX 590, Nvidia GTX 690, Nvidia GTX TITAN; and 3 CPU devices: Intel i5-2430M, Intel i5-4570, i7-3820. Each platform was unloaded, frequency governors disabled, and benchmark processes set to the highest priority available to the task scheduler. Datasets and programs were stored in an in-memory file system. For each program, dataset sizes of size 512 × 512, 1024 × 1024, 2048 × 2048, and 4096 × 4096 were used. A minimum of 30 samples were recorded for each scenario and workgroup size.

Program behavior is validated by comparing program output against a gold standard output collected by executing each of the real-world benchmarks programs using the *baseline* workgroup size (defined below). The output of real-

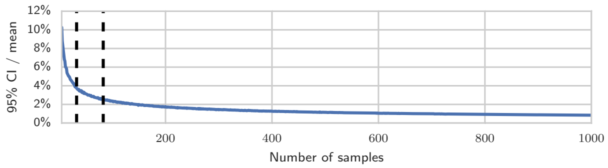


Figure 8: Ratio of 95% confidence interval to mean as a function of sample size. Two dashed lines indicate the confidence intervals at the minimum (3.7%) and mean (2.5%) sample size found in the experimental dataset.

world benchmarks with other workgroup sizes is compared to this gold standard output to test for correct program execution.

6. Evaluation

This section evaluates the performance of OmniTune when tasked with selecting workgroup sizes for SkelCL stencil codes. The experimental results consist of measured runtimes for a set of *test cases*, where each test case τ_i consists of a scenario, workgroup size pair $\tau_i = (s_i, w_i)$, and is associated with a *sample* of observed runtimes from multiple runs of the program. A total of 269,813 test cases have been evaluated with an average sample size of 83 (min 33, total 16,917,118). This represents an exhaustive enumeration of the workgroup size optimization space for 429 scenarios, with an average of 629 (max 7,260) unique workgroup sizes for each scenario.

6.1 Runtime Noise

First we examine the noise present in program runtime measurements. The complex interaction between processes competing for the finite resources of a system introduces many sources for such noise. Figure 7 plots the distributions of 1000 runtimes recorded for 9 SkelCL stencil kernels, (a)–(i). The plots show that the distribution of runtimes is not Gaussian; rather, it is sometimes multimodal, and generally skewed to the lower end of the runtime range, with a long "tail" to the right. This fits our intuition that programs have a hard *minimum* runtime enforced by the time taken to execute the instructions of a program, and that noise introduced to the system extends this runtime. For example, preempting an OpenCL process on a CPU so that another process may run may cause the very long tail visible in Figure 7a.

It is important to ensure a sufficiently large sample size when performing optimisations based on empirical performance data. A recommendation of ≥ 30 samples is common in the benchmarking literature [9]. Our experimental results support this recommendation: Figure 8 plots the ratio of 95% confidence interval to the sample mean for different sample sizes, showing a 50% reduction in confidence interval size when increasing the sample size from 10 to 30. In this experimental dataset, the ratio of confidence interval to mean at the smallest sample size (33) is 3.7%, and 2.5% at the mean sample size (83).

6.2 OpenCL Workgroup Size Optimization Space

We can calculate an upper bound for the performance impact of the workgroup size parameter by comparing the average runtimes of the *best* and *worst* workgroup size for a single scenario. Applying this to all scenarios, we find the average speedup upper bound to be 15.14× (min 1.03×, max 207.72×). This demonstrates the importance of tuning stencil workgroup sizes — if chosen incorrectly, the runtime of stencil programs can be extended by up to 207.72×. Note that for 5 of the scenarios, the speedup of the best over worst workgroup sizes is less than 5%. For these scenarios, there is little benefit to autotuning; however, this represents only 1.1% of the tested scenarios. For 50% of the scenarios, the speedup of the best over worst workgroup sizes is greater than 6.19×.

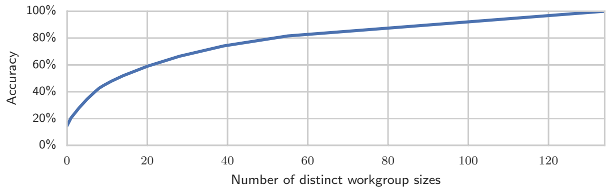


Figure 9: Accuracy compared to the oracle as a function of the number of unique workgroup sizes. The greatest accuracy that can be achieved using a single statically chosen workgroup size is 15%. Achieving 50% oracle accuracy requires a minimum of 14 distinct workgroup sizes.

For the purposes of evaluating autotuning, we use three *baselines* to compare program runtimes against. The relative performance of a workgroup size for a particular scenario is compared against runtimes for each of three parameters:

- *Oracle* — The *oracle* workgroup size is the workgroup size which provided the lowest mean runtime for a given scenario. Speedup relative to the oracle is in the range $0 \leq x \leq 1$, so this can be referred to as *performance*.
- *Baseline* — The *baseline* parameter is the workgroup size which provides the best overall performance while being legal for all scenarios. Such a baseline value represents the *best* possible performance which can be achieved using a single, statically chosen workgroup size. By defining $W_{safe} \in W$ as the intersection of legal workgroup sizes, the baseline $\bar{w}$ can be found using:

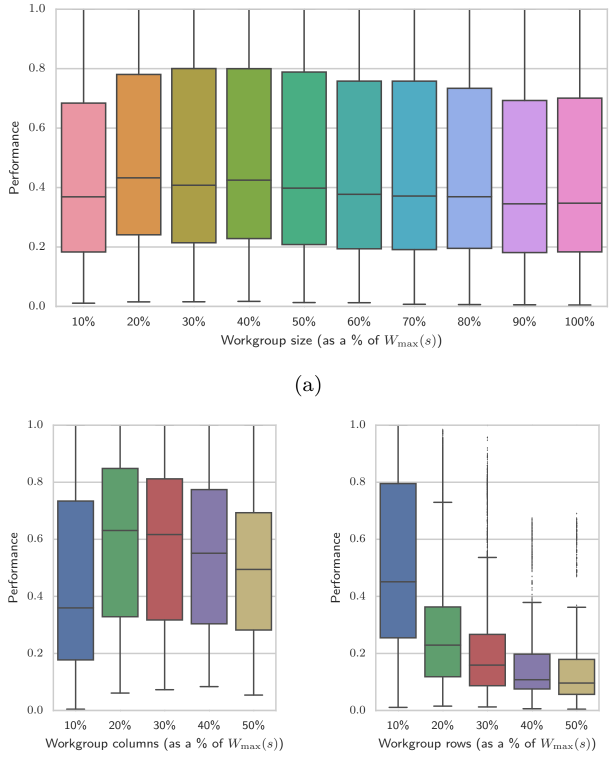
$$W_{safe} = \cap \{W_{legal}(s) | s \in S\} \tag{7}$$

$$\bar{w} = \underset{w \in W_{safe}}{\arg\max}\, \bar{p}(w) \tag{8}$$

  For our experimental data, we find this value to be $w_{(4 \times 4)}$.
- *Human expert* — In the original implementation of the SkelCL stencil skeleton [7], Steuwer et al. selected a workgroup size of $w_{(32 \times 4)}$, based on an evaluation of 4 stencil programs on a Tesla S1070 system.

Across the 429 scenarios tested, there are 135 unique *oracle* workgroup sizes. This demonstrates the difficulty in attempting to statically tune for *optimal* parameter values, since 31.5% of scenarios have different oracle workgroup sizes. Figure 9 shows that a minimum of 14 distinct workgroup sizes are needed to achieve just 50% of the oracle accuracy, although it is important to make the distinction that oracle *accuracy* and *performance* are not equivalent.

We find that the *human expert* selected workgroup size is invalid for 2.6% of scenarios, as it is refused by 11 test cases. By device, these are: 3 on the GTX 690, 6 on the i5-2430M,

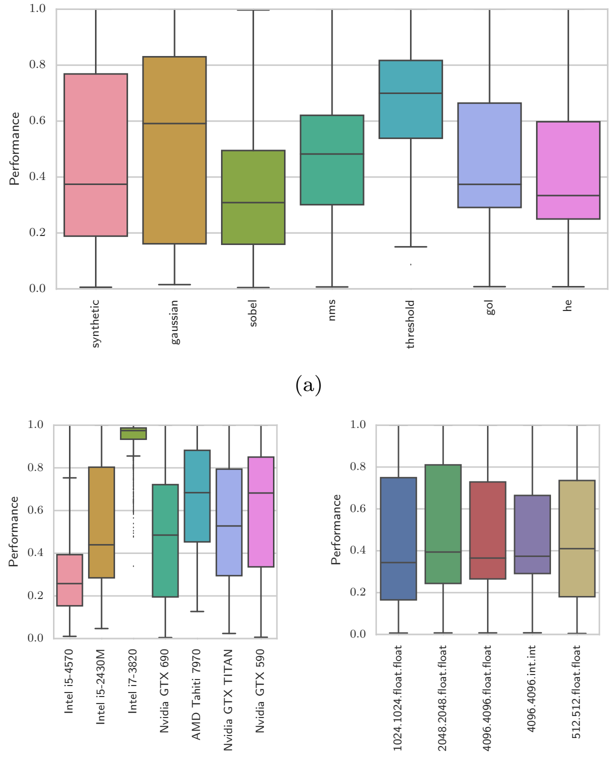


(a)

(b)

(c)

Figure 10: Comparing performance of workgroup sizes relative to the oracle as a function of: (a) maximum legal size, (b) number of columns, and (c) number of rows. Each workgroup size is normalized to the maximum allowed for that scenario, $W_{\max}(s)$. There is no clear correlation between workgroup size and performance.



(a)

(b)

(c)

Figure 11: Performance relative to the oracle of workgroup sizes across all test cases, grouped by: (a) kernels, (b) devices, and (c) datasets. The performance impact is not consistent across kernels, devices, or datasets. The Intel i7-3820 has the lowest performance gains from tuning workgroup size.

and 2 on the i5-4570. For the purpose of comparing performance against human experts, we will ignore these test cases, but it demonstrates the utility of autotuning not just for maximizing performance, but ensuring program reliability. For the scenarios where the human expert workgroup size *is* legal, it achieves an impressive geometric mean of 79.2% of the oracle performance. The average speedup of oracle workgroup sizes over the workgroup size selected by a human expert is 1.37× (min 1.0×, max 5.17×).

The utility of the *baseline* workgroup size is that it represents the best performance that can be achieved through static tuning. The baseline workgroup size achieves only 24% of the maximum performance. Figures 10 and 11 show box plots for the performance of all workgroup sizes using different groupings: ratio of maximum workgroup size, kernel, device, and dataset. The plots show the median performance, interquartile range, and outliers. What is evident is both the large range of workgroup size performances (i.e. the high performance upper bounds), and the lack of obvious correlations between any of the groupings and performance.

6.3 Autotuning Workgroup Sizes

To evaluate the performance of machine learning-enabled autotuning of SkelCL stencils, we partition the experimental data into *training* and *test* sets. The training set is used to build the machine learning model. The predicted workgroup size for each entry in the test set is then used to evaluate the autotuning performance. We use 5 different approaches to partitioning the test and training data, which each test different aspects of the system. The first is a k-fold cross validation, a standard machine learning model validation technique in which the set of all data is shuffled and then divided into k equally sized validation sets. Each validation set is used to test a model trained on the remaining data [8]. In our evaluation we use a value of $k = 10$. The second technique is to partition the data such that it consists of data gathered from synthetic benchmarks, and use data collected from real-world benchmarks to test. This tests the utility of training using synthetically generated benchmarks. The third, forth, and fifth approaches involve creating leave-one-out training sets for all data grouped by device, kernel, and dataset, respectively. This tests the ability to successfully apply prior knowledge about other devices, kernels, and datasets, to new unseen cases. For example, of the n devices used to collect performance data, the model is trained on data from $n-1$ devices, and tested against data from the n^{th}. Table 1 summarizes the results of evaluating the autotuner using each of the different validation techniques.

The autotuner achieves good performance, with average speedups over the baseline across all validation sets range between 4.79× and 5.65×. Importantly, the performance when validating across devices, kernels, and datasets, is comparable to the 10-fold validation. This demonstrates that the autotuner is capable of learning *across* these targets. So if

Training Dataset	Performance	Speedup over Baseline	Speedup over Human Expert
10-fold	92%	5.65×	1.26×
Synthetic	92%	4.79×	1.13×
$n-1$ Device	85%	5.23×	1.17×
$n-1$ Kernel	89%	5.43×	1.21×
$n-1$ Dataset	91%	5.63×	1.25×
Average	**90%**	**5.45×**	**1.22×**

Table 1: Performance results using a J48 Decision Tree across different validation sets. Note that the human expert selected workgroup size is invalid for 2.6% of test cases, which we excluded for the purpose of performance comparisons against human expert.

the autotuner is deployed to a system for which it has no prior knowledge, it does not suffer a significant drop in performance. The same is true for an unseen kernel, or dataset type. This, combined with the distributed datasets provided by the OmniTune framework, demonstrates the utility of autotuning at the skeletal level, allowing machine learning to successfully learn predictions across unseen programs, kernels, and datasets.

Classification using decision trees is a lightweight process (they can be implemented using a chain of `if/else` statements). The measured overhead of autotuning is 2.5ms, of which only 0.3ms is required for classification using Weka, although an optimized decision tree implementation could reduce this further. The remaining 2.2ms is required for feature extraction and the inter-process round trip between the OmniTune server and client.

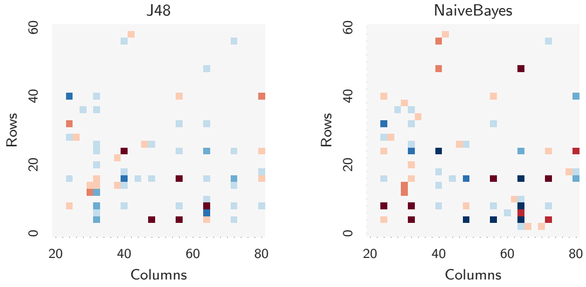
6.4 OmniTune Extensibility

The client-server architecture OmniTune neatly separates the autotuning logic from the target application. This makes adjusting the autotuning methodology a simple process. To demonstrate this, we changed the machine learning algorithm from a J48 decision tree to a Naive Bayes classifier, and duplicated the evaluation. This required only a single line of source code in the OmniTune server extension to be changed. Figure 12 visualizes the differences in autotuning predictions when changing between these two classifiers. While the average performances of the two classifiers is comparable, the distribution of predictions is not. For example, the Naive Bayes classifier predicted the human expert selected workgroup size of $w_{(32 \times 4)}$ more frequently than it was optimal, while the decision tree predicted it less frequently. Selection of machine learning algorithms has a large impact on the effectiveness of autotuning, and the OmniTune client-server design allows for low cost experimenting with different approaches. In future work we will investigate meta-tuning techniques for selecting autotuning algorithms.

6.5 Summary

In this section we have explored the performance impact of the workgroup size optimization space, and the effectiveness of autotuning using OmniTune to exploit this. By comparing the relative performance of an average of 629 workgroup sizes for each of 429 scenarios, the following conclusions can be drawn:

- The performance gap between the best and workgroup sizes for a particular combination of hardware, software, and dataset is up to 207.72×.
- Not all workgroup sizes are legal, and the space of legal workgroup sizes cannot statically be determined. Adaptive tuning is required to ensure reliable performance.
- Statically tuning workgroup size fails to extract the potential performance across a range of programs, architectures, and datasets. The best statically chosen workgroup size achieves only 26% of the optimal performance.
- Workgroup size prediction using a decision tree achieves an average 90% of the optimal performance.
- Auotuning provides performance portability across programs, devices, and datasets. The performance of predicted workgroup sizes for unseen devices is within 8% of the performance for known devices.



(a) (b)

Figure 12: Heatmaps of autotuner predictions for a subset of the explored optimization space ($w_c < 80, w_r < 80$) using two different classifiers. The shading in each cells indicates if it is predicted less frequently (blue), ore more frequently (red) than it is optimal. Color gradients are normalized across plots.

7. Related Work

Early work in autotuning applied iterative search techniques to the space of compiler optimisations [3, 10]. Since then, machine learning techniques have been successfully employed to reduce the cost of iterative compilation [11–13]. However, optimizing GPGPU programs presents different challenges to that of traditional CPU programming. Ryoo et al. demonstrated speedups of up to 432× for matrix multiplication in CUDA through the appropriate use of zero-overhead thread scheduling, memory bandwidth, and thread grouping. The importance of proper exploitation of local shared memory and synchronization costs is explored in [15]. In [5], data locality optimisations are automated using a description of the hardware and a memory-placement-agnostic compiler. Magni, Dubach, and O'Boyle use a machine learning model to predict optimal thread coarsening factors of OpenCL kernels in [16], demonstrating speedups between 1.11× and 1.33×.

Auotuning transformations for stencil codes are explored in [17] using an IR to represent stencils and a CUDA code generator at the backend. However, they do not optimize for the GPU memory hierarchy, using only global memory. In [6], Lutz, Fensch, and Cole demonstrate that optimal swapping strategy for multi-GPU stencils depends on the size of the grid, the number of partitions, and the connection mechanism (e.g. PCI express). Autotuning for algorithmic skeletons is performed using Nearest Neighbor classification and Principle Component Analysis in [18].

OpenTuner is a general purpose toolkit for autotuning which uses ensemble search techniques to reduce the cost of exploring an optimization space, rather than the machine learning approach taken in this work [19]. Since OpenTuner does not *learn* optimization spaces as OmniTune does, performance data is not shared across devices. This means that the search for performant parameter values must be performed by each new device to be autotuned. Our approach combines machine learning with distributed training sets so that new users automatically benefit from the collective tuning experience of other users, which reduces the time to deployment.

A "big data" driven approach to autotuning is presented in [20]. The authors propose the use of "Collective optimization" to leverage training experience across devices, by sharing performance data, datasets and additional metadata about experimental setups. In addition to the mechanism for sharing training datasets, our system provides the capabilities of performing autotuning at runtime using a lightweight inter-process communication interface. Additionally, Collective Mind uses a NoSQL JSON format for storing datasets. The relational schema used in OmniTune offers greater scaling performance and lower storage overhead.

8. Conclusions

As the trend towards increasingly programmable heterogeneous architectures continues, the need for high level, accessible abstractions to manage such parallelism will continue to grow. Autotuning proves to be a valuable aid for achieving these goals, provided that the burden of development and collecting performance data is lifted from the user. The system presented in this paper aims to solve this issue by providing a generic interface for implementing machine learning-enabled autotuning. OmniTune is a novel framework for autotuning which has the benefits of a fast, "always-on" interface for client applications, while being able to synchronize data with global repositories of knowledge which are built up across devices. To demonstrate the utility of this framework, we implemented a frontend for predicting the workgroup size of OpenCL kernels for SkelCL stencil codes. This optimization space is complex, non linear, and critical for the performance of stencil kernels. Selecting the correct workgroup size is difficult — requiring a knowledge of the kernel, dataset, and underlying architecture. The implemented autotuner achieves 92% of the maximum performance, and provides performance portability, even achieving an average of 85% of the maximum performance when deployed on a device for which it has no prior training data. By performing autotuning at the skeletal level, the system is able to exploit underlying similarities between pattern implementations which are not shared in unstructured code. In future work we will explore methods for collaborative exploration of optimization spaces in parallel across multiple cooperating devices, and targeting multiple parameters simultaneously.

Acknowledgments

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References

[1] J Enmyren and CW Kessler. "SkePU: a multi-backend skeleton programming library for multi-GPU systems". In: *HLPP*. ACM, 2010, pp. 5–14.

[2] Ricardo Marques, Hervé Paulino, Fernando Alexandre, and Pedro D. Medeiros. "Algorithmic skeleton framework for the orchestration of GPU computations". In: *Euro-Par 2013 Parallel Processing*. Vol. 8097 LNCS. Springer, 2013, pp. 874–885.

[3] T Kisuki, Niels Bohrweg, and Campus De Beaulieu. "A Feasibility Study in Iterative Compilation". In: *High Performance Computing*. Springer, 1999, pp. 131–132.

[4] Michel Steuwer, Philipp Kegel, and Sergei Gorlatch. "SkelCL - A Portable Skeleton Library for High-Level GPU Programming". In: *IPDPSW*. IEEE, May 2011, pp. 1176–1182.

[5] Guoyang Chen and Bo Wu. "PORPLE: An Extensible Optimizer for Portable Data Placement on GPU". In: *MICRO*. IEEE, 2014, pp. 88–100.

[6] Thibaut Lutz, Christian Fensch, and Murray Cole. "PARTANS: An Autotuning Framework for Stencil Computation on Multi-GPU Systems". In: *TACO* 9.4 (2013), p. 59.

[7] Michel Steuwer, Michael Haidl, Stefan Breuer, and Sergei Gorlatch. "High-level programming of stencil computations on multi-GPU systems using the SkelCL library". In: *Parallel Processing Letters* 24.03 (2014), p. 1441005.

[8] Jiawei Han, Micheline Kamber, and Jian Pei. *Data mining: concepts and techniques*. Elsevier, 2011.

[9] Andy Georges, Dries Buytaert, and Lieven Eeckhout. "Statistically Rigorous Java Performance Evaluation". In: *ACM SIGPLAN*. Vol. 42. 10. New York, NY, USA: ACM, Oct. 2007, p. 57.

[10] F. Bodin, T. Kisuki, P.M.W. Knijnenburg, M.F.P. O'Boyle, and E. Rohou. "Iterative compilation in a non-linear optimisation space". In: *Workshop on Profile Directed Feedback-Compilation, PACT*. 1998.

[11] Felix Agakov, Edwin Bonilla, John Cavazos, Björn Franke, Grigori Fursin, Michael FP O'Boyle, John Thomson, Marc Toussaint, and Christopher KI Williams. "Using Machine Learning to Focus Iterative Optimization". In: *CGO*. IEEE Computer Society, 2006, pp. 295–305.

[12] Mark Stephenson, Martin Martin, and Una-may O Reilly. "Meta Optimization: Improving Compiler Heuristics with Machine Learning". In: *ACM SIGPLAN Notices* 38.5 (2003), pp. 77–90.

[13] Grigori Fursin, Yuriy Kashnikov, Abdul Wahid Memon, Zbigniew Chamski, Olivier Temam, Mircea Namolaru, Elad Yom-Tov, Bilha Mendelson, Ayal Zaks, Eric Courtois, Francois Bodin, Phil Barnard, Elton Ashton, Edwin Bonilla, John Thomson, Christopher K. I. Williams, and Michael O'Boyle. "Milepost GCC: Machine Learning Enabled Self-tuning Compiler". In: *IJPP* 39.3 (Jan. 2011), pp. 296–327.

[14] Shane Ryoo, Christopher I. Rodrigues, Sara S. Baghsorkhi, Sam S. Stone, David B. Kirk, and Wen-mei W. Hwu. "Optimization principles and application performance evaluation of a multithreaded GPU using CUDA". In: *PPoPP* (2008), p. 73.

[15] Victor W. Lee, Per Hammarlund, Ronak Singhal, Pradeep Dubey, Changkyu Kim, Jatin Chhugani, Michael Deisher, Daehyun Kim, Anthony D. Nguyen, Nadathur Satish, Mikhail Smelyanskiy, and Srinivas Chennupaty. "Debunking the 100X GPU vs. CPU myth". In: *ACM SIGARCH Computer Architecture News* 38 (2010), p. 451.

[16] Alberto Magni, Christophe Dubach, and Michael O'Boyle. "Automatic optimization of thread-coarsening for graphics processors". In: *PACT*. 2014, pp. 455–466.

[17] Shoaib Kamil, Cy Chan, Leonid Oliker, John Shall, and Samuel Williams. "An auto-tuning framework for parallel multicore stencil computations". In: *IPDPS* (2010).

[18] Alexander Collins, Christian Fensch, Hugh Leather, and Murray Cole. "MaSiF: Machine Learning Guided Auto-tuning of Parallel Skeletons". In: *HiPC* (Dec. 2013), pp. 186–195.

[19] Jason Ansel, Shoaib Kamil, Una-may O Reilly, Saman Amarasinghe, Jason Ansel, and Una-may O Reilly. "OpenTuner: An Extensible Framework for Program Autotuning". In: *PACT*. 2013.

[20] Grigori Fursin, Renato Miceli, Anton Lokhmotov, Michael Gerndt, Marc Baboulin, Allen D Malony, Zbigniew Chamski, Diego Novillo, and Davide Del Vento. "Collective Mind: Towards practical and collaborative auto-tuning". In: *Scientific Programming* 22.4 (2014), pp. 309–329.