Autotuning NVCC Parameters in the Julia Language

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August 24, 2017

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The slides and all source code are hosted at GitHub:

- `github.com/phrb/nvidia-workshop-autotuning`

Outline

1. Introduction to Autotuning
2. Examples & Results on Different Domains
3. An Autotuning Library in the Julia Language
4. NVCC Flag Autotuner

Objectives of this Workshop

We want to enable CUDA programmers to autotune compiler parameters:

- Using a free, open-source autotuner
- Plug your application in and achieve from a few % up to $4\times$ speedup
- We are willing to help!

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If you use our autotuner, consider reporting your results back to us:

- Which GPUs did you target?
- What speedups did you achieve?
- Did you add new compiler parameters?

Autotuning: Optimization as a Search Problem

Casting program optimization as a search problem:

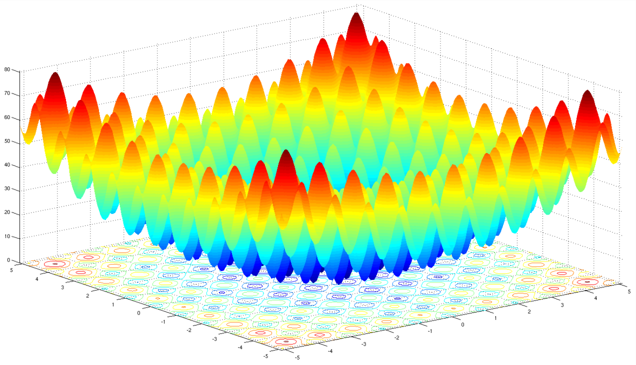
Search Spaces:

- Algorithm Selections
- Program Configurations
- . . .

Search Objectives:

- Minimize execution time
- Maximize usage of resources
- . . .

The search spaces created by program optimization problems can be difficult to explore



Rastrigin function, with global minimum $f(0, 0) = 0$

Search Spaces & Techniques

System	Domain	Technique
ATLAS	Dense Linear Algebra	Exhaustive
Insieme	Compiler	Genetic Algorithm
SPIRAL	DSP Algorithms	Pareto Active Learning
Active Harmony	Runtime	Nelder-Mead
Periscope	HPC Applications	Various
OpenTuner	Domain-Agnostic	Ensemble

Table 1: Some autotuning systems, their domains and techniques

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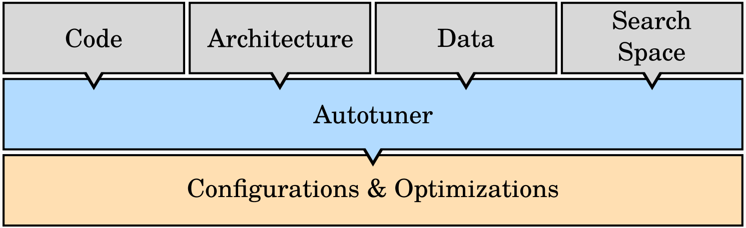
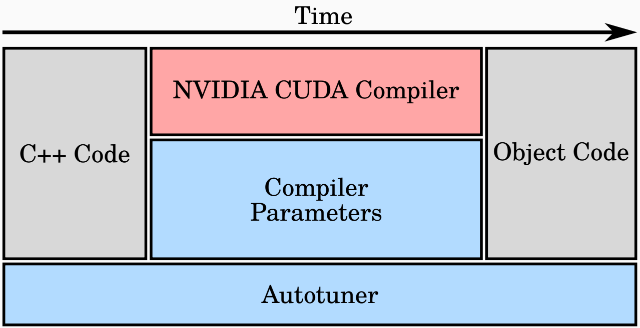
Table 1: Some autotuning systems, their domains and techniques

- Different problem domains generate different search spaces
- No single solution for all domains
- Search techniques can be composed: OpenTuner
- Independent searches can be parallelized and distributed

Autotuning: Abstract Model



NVIDIA CUDA Compiler: From CUDA C++ to Object Code



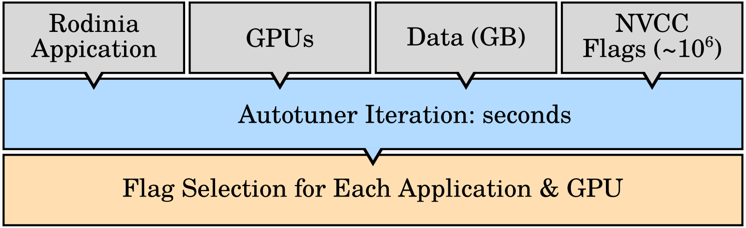
- We tuned applications from the Rodinia Benchmark Suite
- C++ $\longrightarrow$ Object Code: takes seconds

Flags in the search space:

Flag	*Step*
no-align-double	NVCC
use_fast_math	NVCC
gpu-architecture	NVCC
relocatable-device-code	NVCC
ftz	NVCC
prec-div	NVCC
prec-sqrt	NVCC

Flag	*Step*
def-load-cache	PTX
opt-level	PTX
fmad	PTX
allow-expensive-optimizations	PTX
maxrregcount	PTX
preserve-relocs	NVLINK

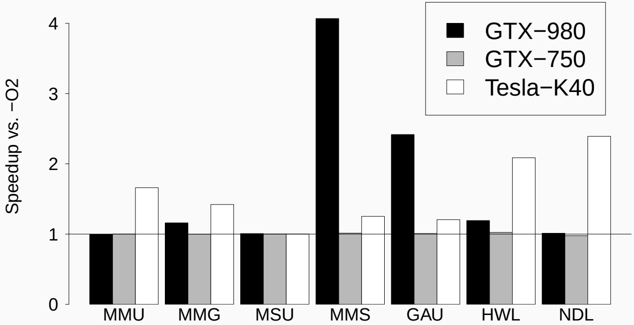
Autotuning: GPUs



1h of tuning $\rightarrow \approx 10^3$ iterations

Results

Most significative speedups for Rodinia applications and matrix multiplication optimizations, after 1.5h of tuning:



We found no globally good parameter selections for specific GPUs or applications

An Autotuning Library in the Julia Language

StochasticSearch

We are developing an autotuning library:

- In the Julia language
- Domain-Agnostic
- Parallel and distributed autotuning
- `github.com/phrb/StochasticSearch.jl`

StochasticSearch: Search Techniques

Multiple simultaneous search techniques share a search space, but not results:

Implemented techniques:

- Simulated Annealing
- Iterated Local Search
- Randomized First Improvement
- Iterative First Improvement
- Iterative Probabilistic Improvement
- Iterative Greedy Construction

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Future techniques:

- Iterative Best Improvement
- Randomized Best Improvement
- Dynamic Local Search
- Tabu Search
- Ant Colony Optimization
- . . .

Why use the Julia Language?

Why the Julia Language?

- High-Level abstractions
- Simple interface for parallel and distributed programming
- Better performance than Python, Matlab, R, . . .

Parallel and Distributed programming:

- Process-based parallelism
- Communication between processes uses channels
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Parallel and Distributed Programming in Julia

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- Process-based parallelism
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- Serialize/Deserialize complex data types
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Simple interface:

- Remote execution on a new process: `remotecall(·)` and `@spawn`
- Channels: `put!(·)` and `take!(·)`

StochasticSearch Example: The Rosenbrock Function

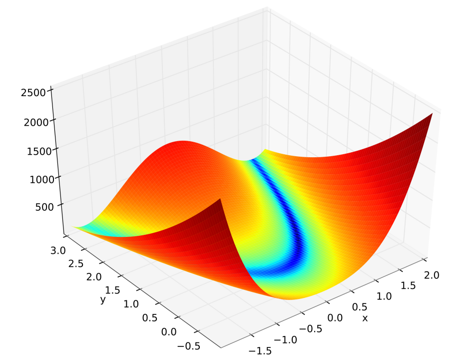
Let's create a Tuning Run using StochasticSearch:

The Rosenbrock function:

- Global minimum $f(1, 1) = 0$
- Many local minima

Components:

- Parameters
- Configurations
- Cost Function



Parameters:

- Represent individual optimizations
- Determine ranges and initial values
- Integers, Booleans, Permutations, Strings, Enumerations, . . .

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Example:

```
FloatParameter(-2.0, 2.0, 0.0, ”i0”)
```

StochasticSearch: Defining Search Spaces & Tuning Runs

Configurations:

- Contain parameters
- Describe the search space
- Associate optimizations with metrics

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Example:

```
configuration = Configuration([FloatParameter(-2.0, 2.0, 0.0, "i0"),
                               FloatParameter(-2.0, 2.0, 0.0, "i1")],
                               "rosenbrock_config")
```

Cost Function:

- Computes costs for each configuration
- Costs are usually expressed in floating point values

StochasticSearch: Defining Search Spaces & Tuning Runs

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Example:

```
function rosenbrock(x::Configuration, parameters::Dict{Symbol, Any})
    return (1.0 - x["i0"].value)^2 + 100.0 * (x["i1"].value - x["i0"].value^2)^2
end
```

StochasticSearch: Defining Search Spaces & Tuning Runs

Tuning Run:

- Selection of search techniques
- Duration & communication

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Example:

```
tuning_run = Run(cost                = rosenbrock,
                 starting_point      = configuration,
                 stopping_criterion  = elapsed_time_criterion,
                 report_after        = 10,
                 reporting_criterion = elapsed_time_reporting_criterion,
                 duration            = 60,
                 methods             = [[:simulated_annealing 1];
                                         [:iterated_local_search 1];
                                         [:randomized_first_improvement 1];])
```

StochasticSearch: More Examples

Short practical examples at `github.com/phrb/StochasticSearch.jl`:

- Rosenbrock
- Sorting Algorithm Cutoff
- Travelling Salesperson Problem
- NVCC Flags

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