Toward Transparent and Parsimonious Methods for Automatic Performance Tuning

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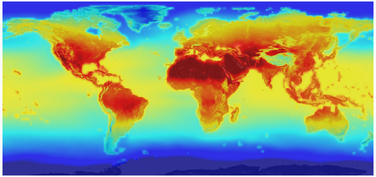
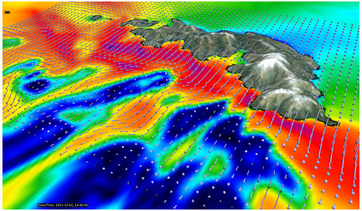
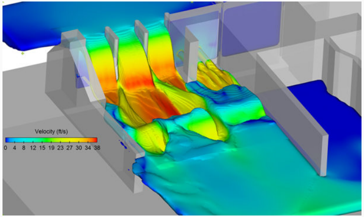
High Performance Computing is Needed at Multiple Scales, . . .

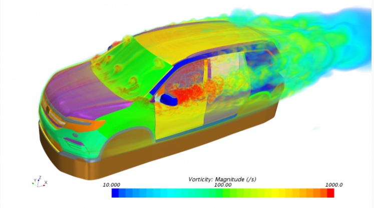
Climate simulation for policies to fight climate change



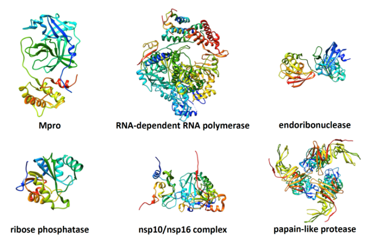


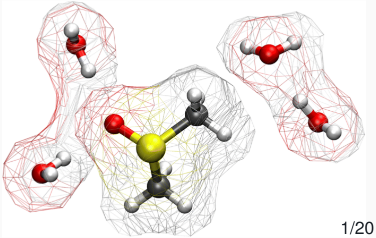
Fluid dynamics for stronger infrastructure and fuel efficiency



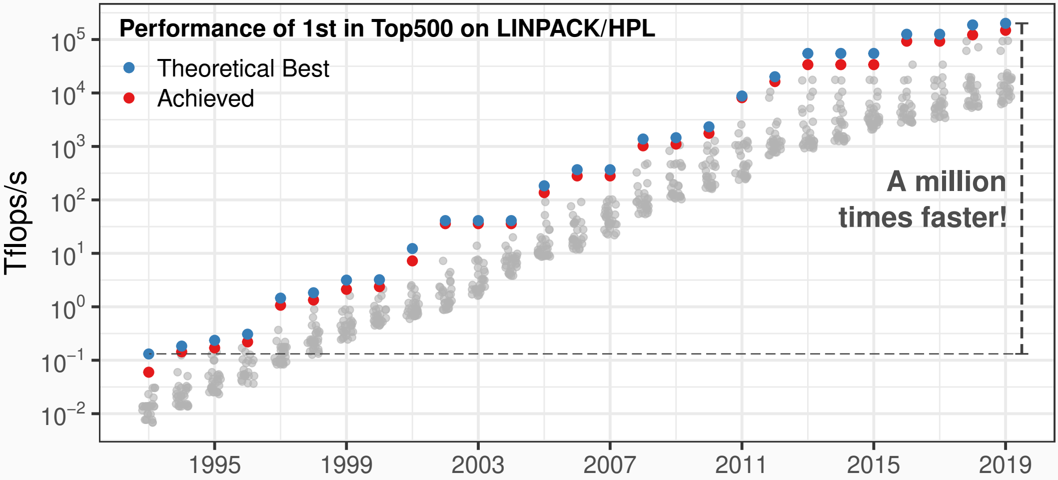


Molecular dynamics for virtual testing of drugs and vaccines

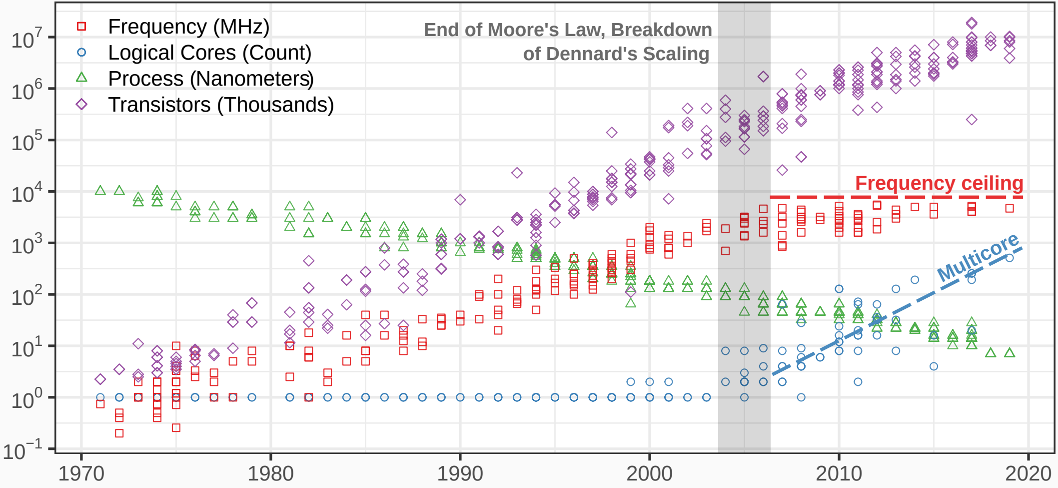




… and the Performance of Supercomputers has so far Improved Exponentially



Software must Improve to Leverage Complexity, and Autotuning can Help



An Autotuning Example: Loop *Blocking* and *Unrolling* for Matrix Multiplication

Optimizing Matrix Multiplication

How to restructure memory accesses in loops to increase throughput by leveraging cache locality?

```
int N = 256;

float A[N][N], B[N][N], C[N][N];
int i, j, k;
// Initialize A, B, C
for(i = 0; i < N; i++){ // Load A[i][]
  for(j = 0; j < N; j++){
    // Load C[i][j], B[][j] to fast memory
    for(k = 0; k < N; k++){




      C[i][j] += A[i][k] * B[k][j];
    }


    // Write C[i][j] to main memory
  }
}
```

An Autotuning Example: Loop *Blocking* and *Unrolling* for Matrix Multiplication

Optimizing Matrix Multiplication

How to restructure memory accesses in loops to increase throughput by leveraging cache locality?

```
int N = 256;
int B_size = 4;
float A[N][N], B[N][N], C[N][N];
int i, j, k, x, y;
// Initialize A, B, C
for(i = 0; i < N; i += B_size){
  for(j = 0; j < N; j += B_size){
    // Load block (i, j) of C to fast memory
    for(k = 0; k < N; k++){
      // Load block (i, k) of A to fast memory
      // Load block (k, y) of B to fast memory
      for(x = i; x < min(i + B_size, N); x++){
        for(y = j; y < min(j + B_size, N); y++){
          C[x][y] += A[x][k] * B[k][y];
        }
      }
    }
    // Write block (i, j) of C to main memory
  }
} // One parameter: B_size
```

An Autotuning Example: Loop *Blocking* and *Unrolling* for Matrix Multiplication

Optimizing Matrix Multiplication

How to restructure memory accesses in loops to increase throughput by leveraging cache locality?

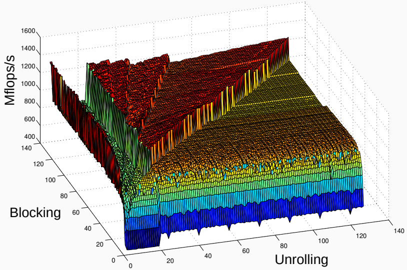
```
int N = 256;
int B_size = 4; int U_size = 2;
float A[N][N], B[N][N], C[N][N];
int i, j, k, x, y;
// Initialize A, B, C
for(i = 0; i < N; i += B_size){
  for(j = 0; j < N; j += B_size){
    // Load block (i, j) of C to fast memory
    for(k = 0; k < N; k++){
      // Load block (i, k) of A to fast memory
      // Load block (k, y) of B to fast memory
      for(x = i; x < min(i + B_size, N); x++){
        for(y = j; y < min(j + B_size, N); y += U_size){
          C[i][y + 0] += A[i][k] * B[k][y + 0];
          C[i][y + 1] += A[i][k] * B[k][y + 1];
        }
      }
    } // Write block (i, j) of C to main memory
  }
} // Two parameters: B_size and U_size
```

An Autotuning Example: Loop *Blocking* and *Unrolling* for Matrix Multiplication

Optimizing Matrix Multiplication

How to restructure memory accesses in loops to increase throughput by leveraging cache locality?

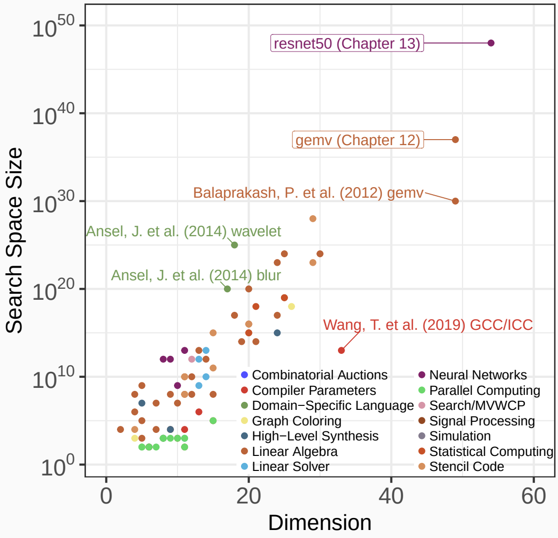
Resulting Search Space



Seymour et al. (2008)

```
int N = 256;
int B_size = 4; int U_size = 2;
float A[N][N], B[N][N], C[N][N];
int i, j, k, x, y;
// Initialize A, B, C
for(i = 0; i < N; i += B_size){
  for(j = 0; j < N; j += B_size){
    // Load block (i, j) of C to fast memory
    for(k = 0; k < N; k++){
      // Load block (i, k) of A to fast memory
      // Load block (k, y) of B to fast memory
      for(x = i; x < min(i + B_size, N); x++){
        for(y = j; y < min(j + B_size, N); y += U_size){
          C[i][y + 0] += A[i][k] * B[k][y + 0];
          C[i][y + 1] += A[i][k] * B[k][y + 1];
        }
      }
    } // Write block (i, j) of C to main memory
  }
} // Two parameters: B_size and U_size
```

Autotuning Problems in Other Domains: Dimension Becomes an Issue



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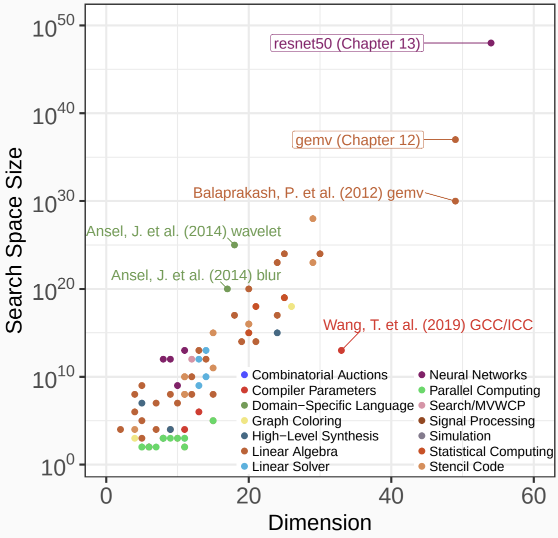
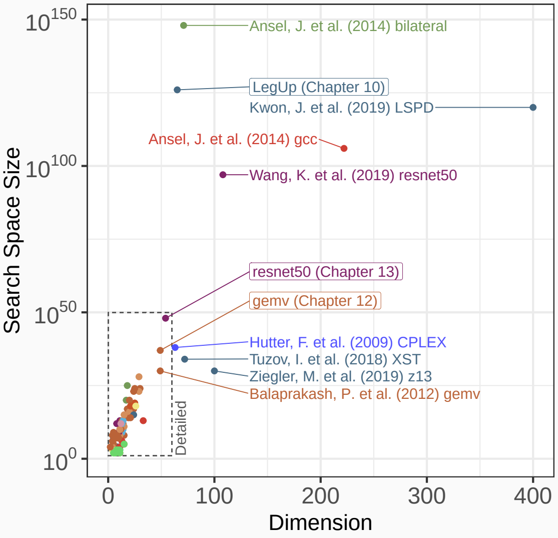




Autotuning as an *Optimization* or *Learning* Problem

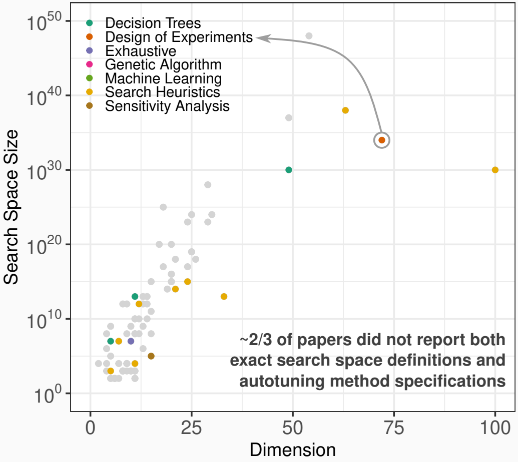
Performance as a Function

Performance: $f : \mathcal{X} \rightarrow \mathbb{R}$

- Parameters: $\mathbf{x} = [x_1 \; \dots \; x_n]^\mathsf{T} \in \mathcal{X}$
- Performance metric: $y = f(\mathbf{x})$

To minimize f, we can adapt proven methods from other domains:

- **Function minimization**, **Learning**: not necessarily parsimonious and transparent
- **Design of Experiments**: can help, but not widely used for autotuning



Toward Transparent and Parsimonious Autotuning

Contributions of this Thesis

- Developing transparent and parsimonious autotuning methods based on the Design of Experiments
- Evaluating different autotuning methods in different HPC domains

Transparent

- Use statistics to justify code optimization choices
- Learn about the search space

Parsimonious

- Carefully choose which experiments to run
- Minimize f using as few measurements as possible

Domain	Method
CUDA compiler parameters	F, D
FPGA compiler parameters	F
OpenCL Laplacian Kernel	F, L, D
SPAPT Kernels	L, D
CNN Quantization	L, D

F: Function Minimization, L: Learning,
D: Design of Experiments

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Applying Methods for Function Minimization

Methods for Function Minimization

Autotuning with Heuristics

- Lack of structured exploration prevented statistical analyses and interpretation

Needle in a Haystack

- Global optimum in 10^{123} configurations?
- Are there better configurations to find?
- For how long should we continue exploring?

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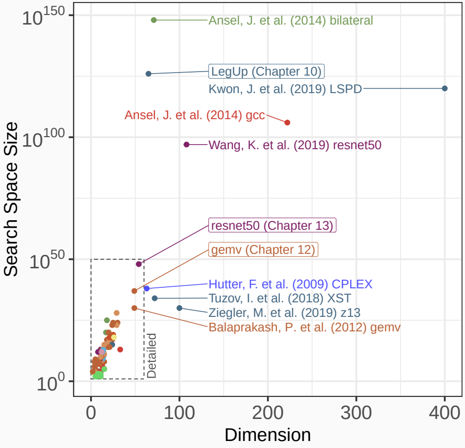

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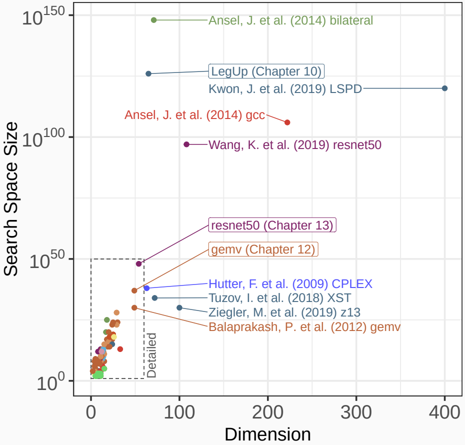


Sequential Design of Experiments

Structure explorations using modeling hypotheses to guide sampling and optimization

Applying Sequential Design of Experiments

Application: OpenCL GPU Laplacian Kernel

Edge Detection with the Laplacian

The OpenCL Kernel

- Highly optimized
- Efficiently parametrized
- Generated by BOAST
- Completely evaluated previously

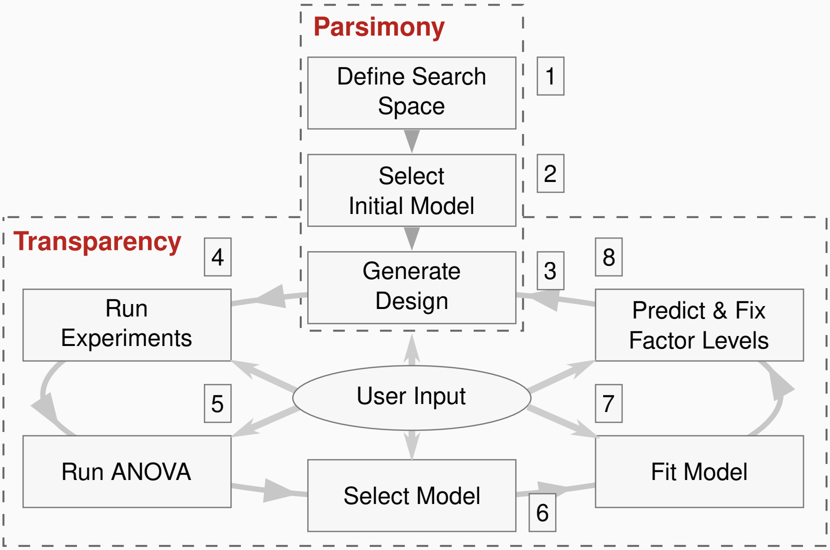
Search Space with 10^4 Valid Configurations

Factor	Levels	Short Description
vector_length	$2^0, \dots, 2^4$	Size of vectors
load_overlap	*true*, *false*	Load overlaps in vectorization
temporary_size	$2, 4$	Byte size of temporary data
elements_number	$1, \dots, 24$	Size of equal data splits
y_component_number	$1, \dots, 6$	Loop tile size
threads_number	$2^5, \dots, 2^{10}$	Size of thread groups
lws_y	$2^0, \dots, 2^{10}$	Block size in y dimension

Performance Metric and Starting Model

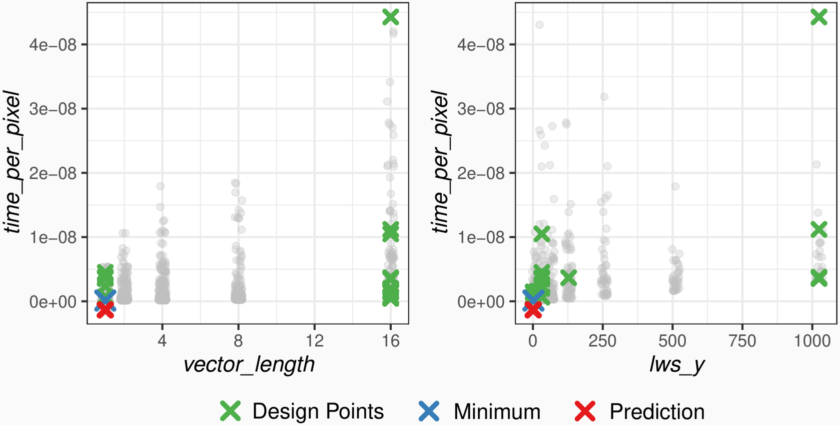
$$\begin{aligned} \mathit{time\_per\_pixel} \sim\ & \mathit{y\_component\_number} + \frac{1}{\mathit{y\_component\_number}} + \\ & \mathit{temporary\_size} + \mathit{vector\_length} + \mathit{load\_overlap} + \\ & \mathit{lws\_y} + \frac{1}{\mathit{lws\_y}} + \mathit{elements\_number} + \frac{1}{\mathit{elements\_number}} + \\ & \mathit{threads\_number} + \frac{1}{\mathit{threads\_number}} \end{aligned}$$

A Transparent and Parsimonious Approach to Autotuning



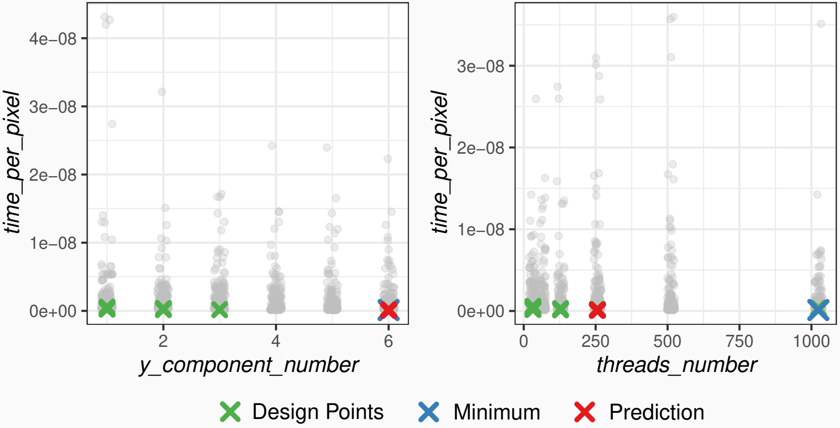
Sequential Approach to Optimization: Refining the Model

Step 1 Fix *vector* and *lws_y*



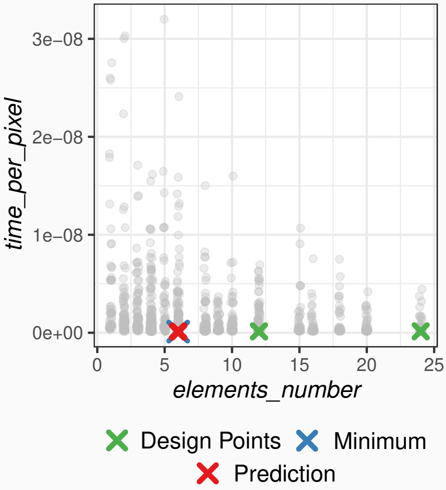
Sequential Approach to Optimization: Refining the Model

Step 2 Fix ***y_cmp.*** and ***threads***



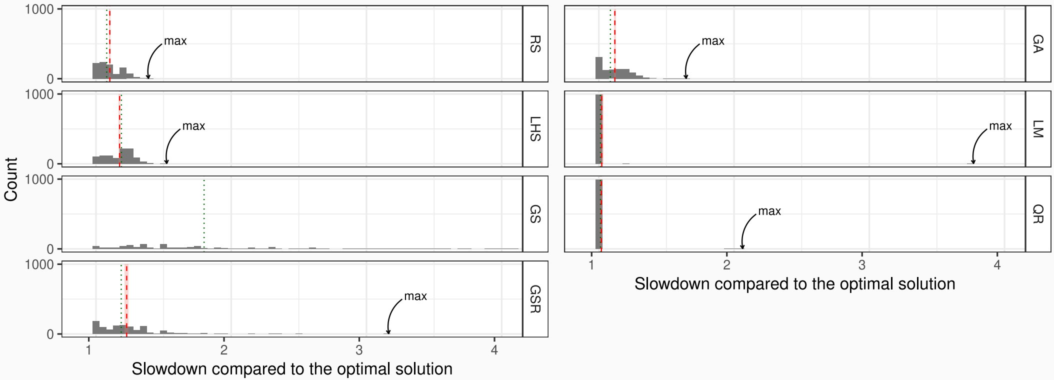
Sequential Approach to Optimization: Transparency

Step 3 Fix *elements*



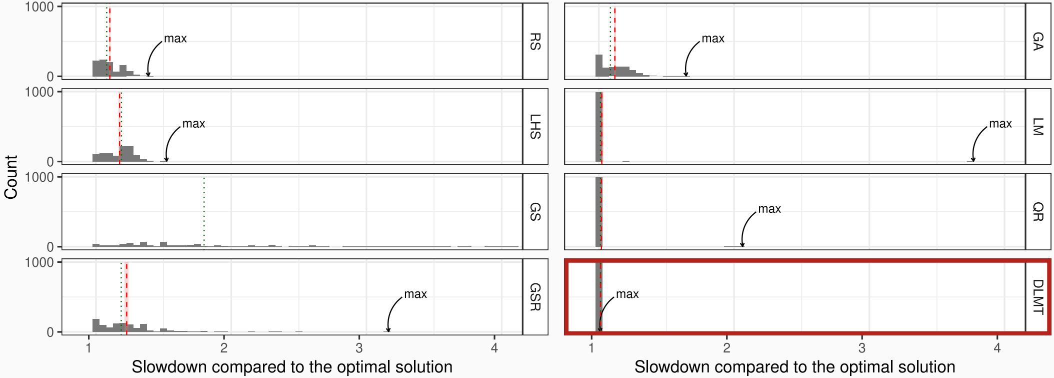
Step	Term	Sum Sq.	F-value	p(>F)
1^{st}	*y_component_number*	2.1×10^{-18}	7.3×10^{-1}	4.1×10^{-1}
	1/y_component_number	4.4×10^{-18}	1.6×10^{0}	2.4×10^{-1}
	vector_length	1.3×10^{-17}	4.4×10^{0}	4.7×10^{-2}
	lws_y	6.9×10^{-17}	2.4×10^{1}	3.5×10^{-4}
	1/lws_y	1.8×10^{-17}	6.2×10^{0}	2.8×10^{-2}
	load_overlap	9.1×10^{-20}	3.2×10^{-2}	8.6×10^{-1}
	temporary_size	7.1×10^{-18}	2.5×10^{0}	1.4×10^{-1}
	elements_number	3.1×10^{-19}	1.1×10^{-1}	7.5×10^{-1}
	1/elements_number	1.3×10^{-18}	4.4×10^{-1}	5.2×10^{-1}
	threads_number	7.2×10^{-18}	2.5×10^{0}	1.4×10^{-1}
	1/threads_number	4.3×10^{-18}	1.5×10^{0}	2.4×10^{-1}
2^{nd}	*y_component_number*	1.2×10^{-19}	2.1×10^{1}	1.4×10^{-3}
	1/y_component_number	1.4×10^{-20}	2.4×10^{0}	1.5×10^{-1}
	load_overlap	4.1×10^{-21}	7.3×10^{-1}	4.1×10^{-1}
	temporary_size	1.4×10^{-21}	2.6×10^{-1}	6.2×10^{-1}
	elements_number	6.0×10^{-22}	1.1×10^{-1}	7.5×10^{-1}
	1/elements_number	2.7×10^{-21}	4.8×10^{-1}	5.0×10^{-1}
	threads_number	7.2×10^{-21}	1.3×10^{0}	2.9×10^{-1}
	1/threads_number	2.9×10^{-20}	5.1×10^{0}	4.0×10^{-2}
3^{rd}	*load_overlap*	7.4×10^{-25}	3.8×10^{0}	1.1×10^{-1}
	temporary_size	1.1×10^{-22}	5.7×10^{2}	2.4×10^{-1}
	elements_number	9.3×10^{-22}	4.7×10^{3}	1.2×10^{-8}
	1/elements_number	3.1×10^{-22}	1.6×10^{3}	1.9×10^{-7}

Results: 1000 Repetitions with a Budget of 120 Measurements



RS: Random Sampling, LHS: Latin Hypercube Sampling, GS: Greedy Search,
GSR: Greedy Search w. Restart, GA: Genetic Algorithm, LM: Linear Model, QR: Quantile Regression

Results: 1000 Repetitions with a Budget of 120 Measurements



RS: Random Sampling, LHS: Latin Hypercube Sampling, GS: Greedy Search,
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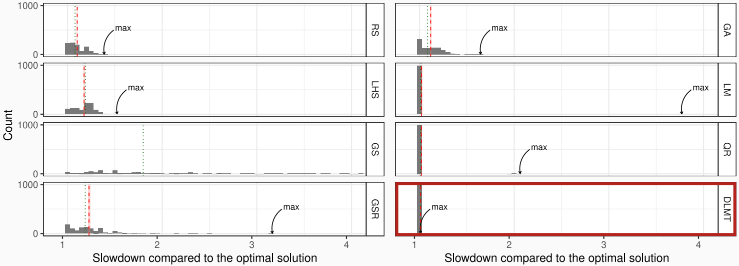
DLMT: D-Optimal Designs, Linear Model w. Transform

Parsimony under Tight Budget Constraints



	Slowdown			Budget	
Method	*Mean*	*Min.*	*Max.*	*Mean*	*Max.*
Random Sampling (RS)	1.10	1.00	1.39	120.00	120
Latin Hypercube Sampling (LHS)	1.17	1.00	1.52	98.92	125
Greedy Search (GS)	6.46	1.00	124.76	22.17	106
Greedy Search w. Restart (GSR)	1.23	1.00	3.16	120.00	120
Genetic Algorithm (GA)	1.12	1.00	1.65	120.00	120
Linear Model (LM)	1.02	1.01	3.77	119.00	119
Quantile Regression (QR)	1.02	1.01	2.06	119.00	119
D-Opt., Linear Model w. Transform (DLMT)	**1.01**	**1.01**	**1.01**	**54.84**	**56**

Design of Experiments and Learning

Random Sampling has Good Performance

- Abundance of local optima?

Motivating Results with the Laplacian Kernel

- Knowledge of the search space
- Good starting model

Broader Evaluation with SPAPT Kernels

- Is there something else to find?
- Can we find it by exploiting structure?

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Different Abstraction Levels

- Algorithm, implementation, dependencies, compiler, OS, hardware
- How to combine them effectively?

Sequential and Incremental Approach

- Definitive search space restrictions
- Experiments and improvements by batch
- Rigid models

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More Flexibility with Gaussian Processes

Balance exploitation of structure with unrestricted exploration

Applying Active Learning with Gaussian Processes

Active Learning with Gaussian Processes

More Flexibility with Gaussian Processes

- No accurate modeling hypotheses needed
- Harder to interpret
- Not always achieves better optimizations
- Effort to build a good model can pay off

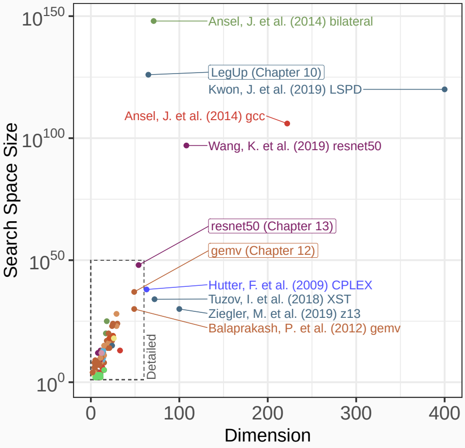
Online Learning

- Deciding where to measure at each new experiment
- Balancing exploitation and exploration
- No restriction to subspaces

Space-filling Designs

- Sampling in high dimension
- Filter to go around constraints

Context: Size of the Search Space



Optimization Methods for Autotuning: An Overview

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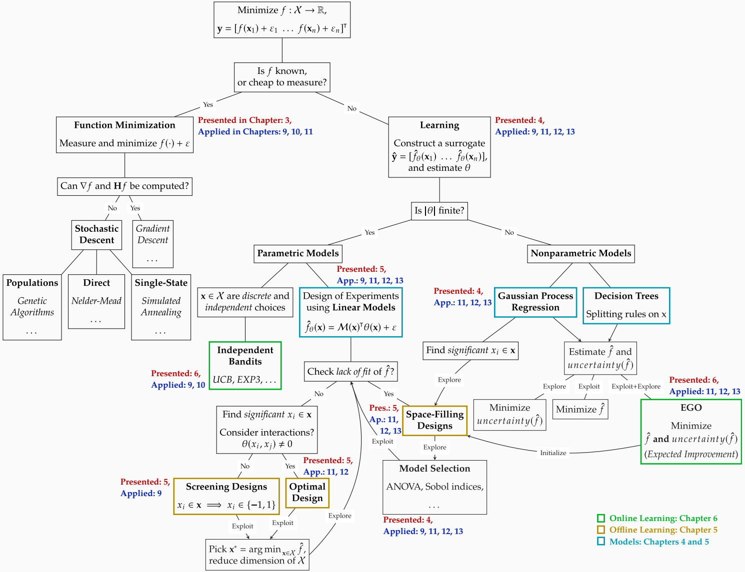
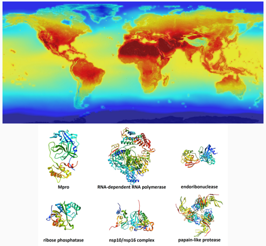
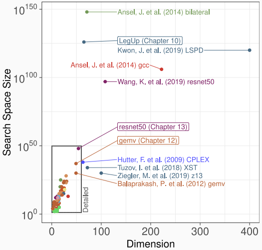


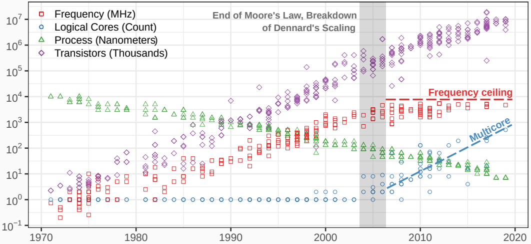
Conclusion

Toward Transparent and Parsimonious Autotuning

Autotuning for High Performance Computing







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CUDA compiler parameters	F, D
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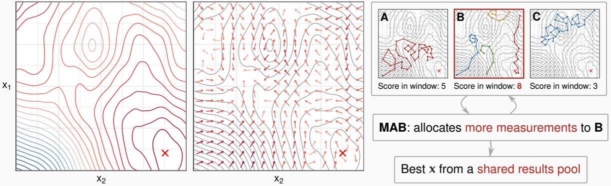
OpenCL Laplacian Kernel	F, L, D
SPAPT Kernels	L, D
CNN Quantization	L, D

F: Function Minimization, L: Learning, D: Design of Experiments

: In this presentation

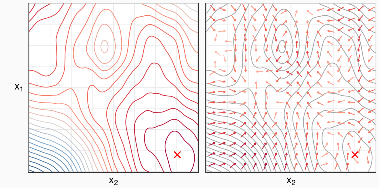
Autotuning Methods Best Suited for Different Contexts

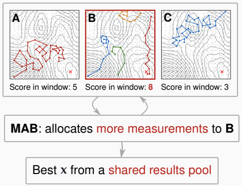


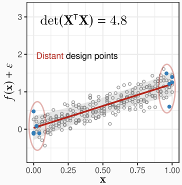
Function Minimization

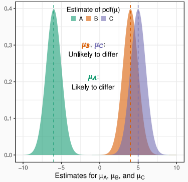
- Optimize f directly
- Hypotheses not always clear
- Use when modeling is hard

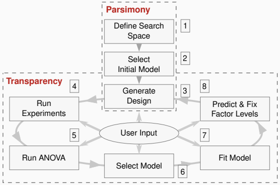
Autotuning Methods Best Suited for Different Contexts











Function Minimization

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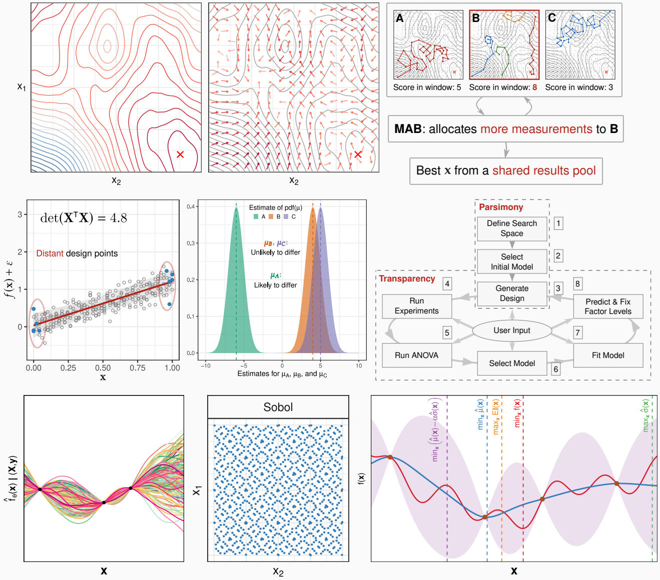
Design of Experiments

- Optimize informed surrogates
- Sequential and incremental
- Use when a model is available

Autotuning Methods Best Suited for Different Contexts



Function Minimization

- Optimize f directly
- Hypotheses not always clear
- Use when modeling is hard

Design of Experiments

- Optimize informed surrogates
- Sequential and incremental
- Use when a model is available

Learning with GPs

- Exploration and exploitation
- Choose experiments online
- Use to build flexible surrogates

Improving Autotuners: Collaborative, Exhaustive, and Reproducible Experiments

Solving Similar Problems

- Each application required redoing work
- Benchmarks such as SPAPT are rare

Exhaustive Measurements

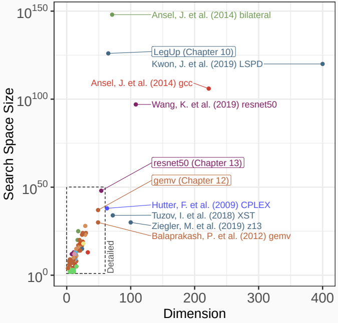
- Completely evaluate a few search spaces

Collaborative Experiments

- Leverage community efforts

Reproducibility

- Notebooks, workflows, archival, and sharing
- Target diverse domains, hardware, software, abstraction levels



Exhaustive and collective experiments are interdependent approaches and can help achieve reproducible autotuning

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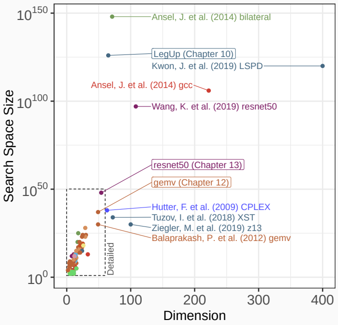

Exhaustive and collective experiments are interdependent approaches and can help achieve reproducible autotuning

Next: Post-doc @ HP Labs, California

Toward Transparent and Parsimonious Methods for Automatic Performance Tuning

Pedro Bruel

October 28 2021

Advisors
Alfredo Goldman (USP)
Arnaud Legrand (CNRS)
Brice Videau (ANL)

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Albert Cohen (Google)
Boyana Norris (UO)
Lucia Drummond (UFF)

Université Grenoble Alpes

CAPES

Hewlett Packard Labs

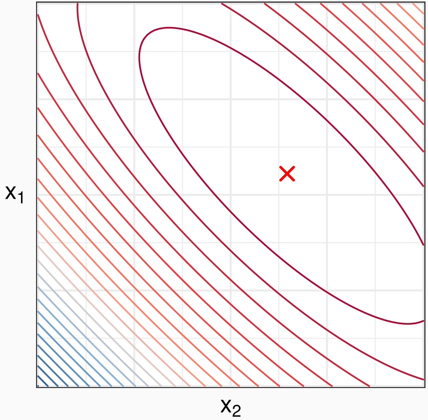
Backup: Applying Methods for Function Minimization

Minimizing Functions using Derivatives and Heuristics

We know or can compute information about f

- Directly measure new $\mathbf{x}_1, \ldots, \mathbf{x}_k, \ldots, \mathbf{x}_n$
- Search for the global optimum

$$f(\mathbf{x}) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2,$$
$$x_1, x_2 \in [-10, 10]$$



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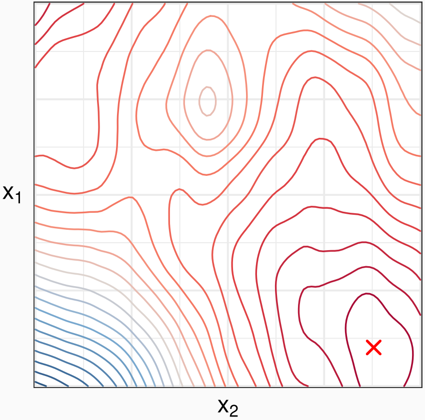

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Strong Hypothesis: we can Compute Derivatives

- $\mathbf{x}_k = \mathbf{x}_{k-1} - \mathbf{H}f(\mathbf{x}_{k-1})\nabla f(\mathbf{x}_{k-1})$

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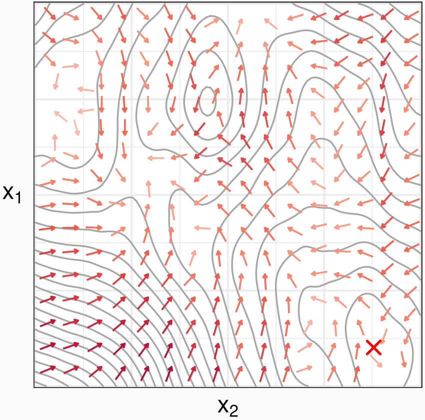

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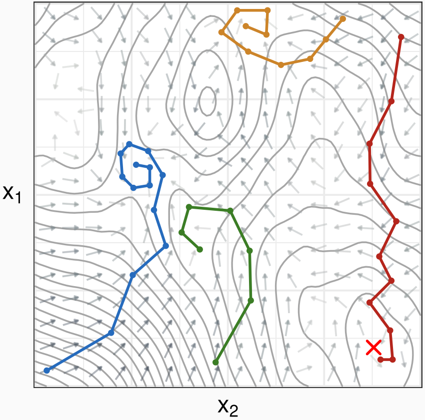

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Hard to State Hypotheses: Search Heuristics

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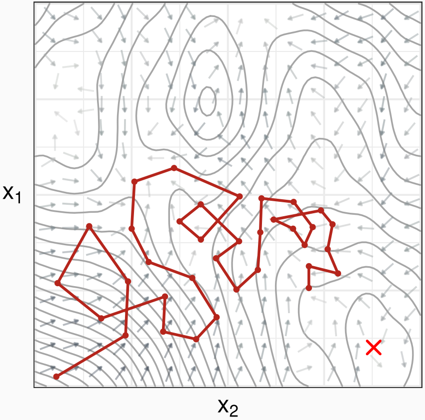

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How to choose a method?

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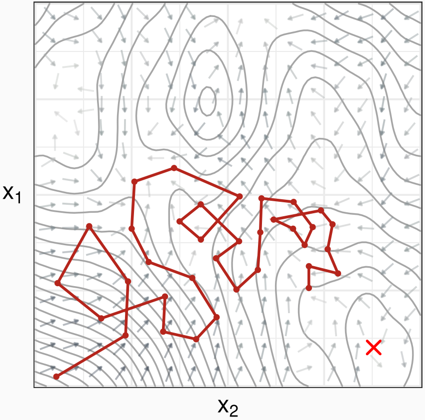
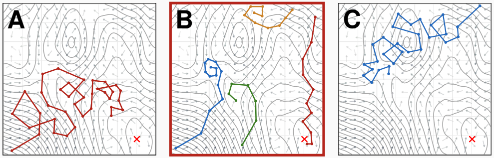


Choosing Methods from an Ensemble

Example of an Ensemble of Methods



Score in window: 5 | Score in window: **8** | Score in window: 3

MAB: allocates more measurements to **B**

Best $\mathbf{x}$ from a shared results pool

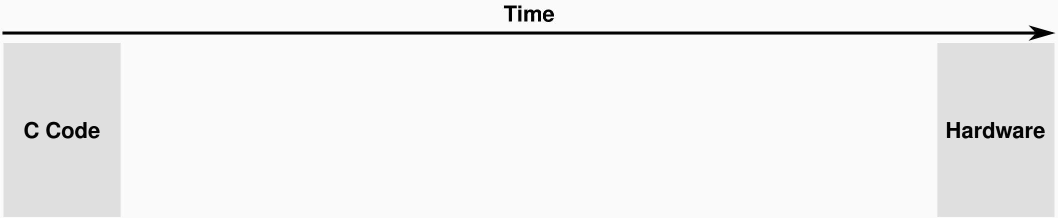
Methods in this Ensemble

- **A**, **C**: Simulated Annealing with different temperature, **B**: Gradient Descent

Minimization of f using OpenTuner

- Coordinated by a Multi-Armed Bandit (MAB) algorithm
- Methods perform measurements proportionally to their score
- Score: the number of times a method found the best $\mathbf{x}$ in a time window
- The best $\mathbf{x}$ over all methods is reported

Application: High-Level Synthesis for FPGAs



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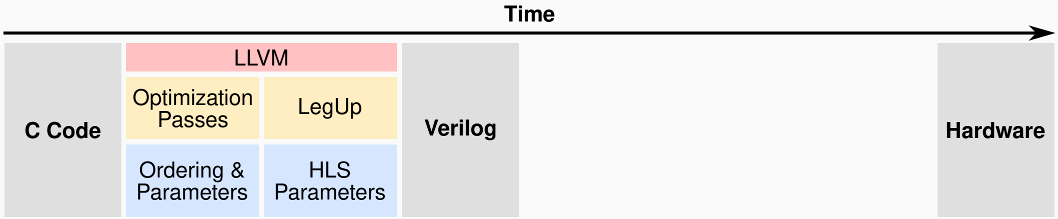

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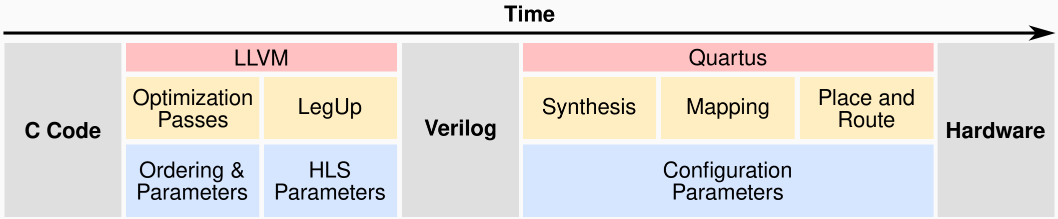

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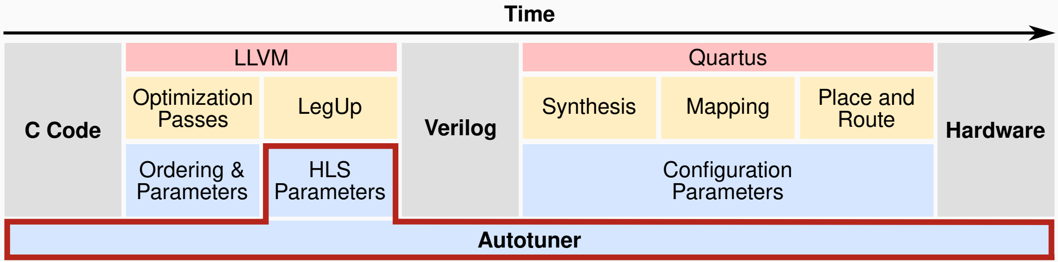

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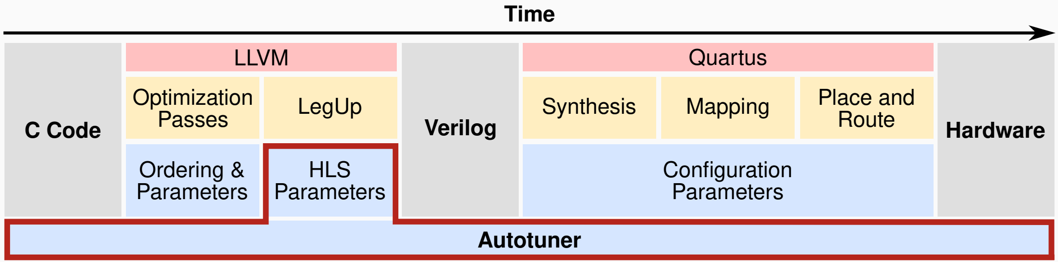
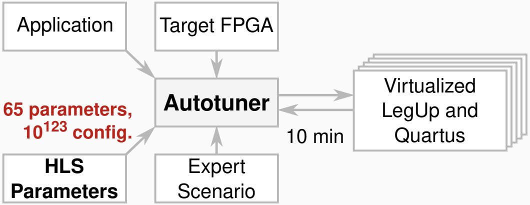


Search Space



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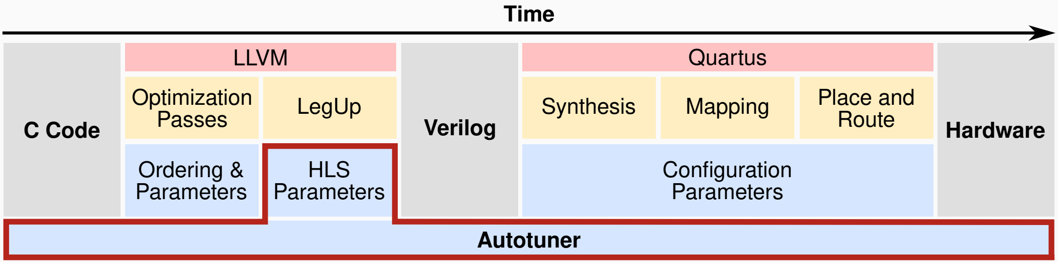

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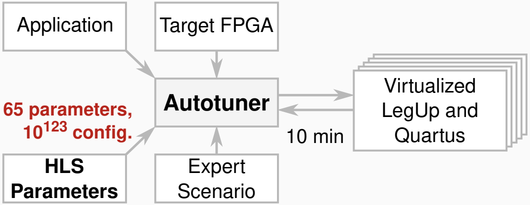


Performance Metrics

- Weighted average of 8 hardware metrics
- Metrics for the usage of registers, memory, DSP units, frequency and clock speed
- An expert devised weights for optimizing for area, latency, performance, or for multiple criteria

Results

Experimental Settings

- 11 problems
- Up to 300 measurements per problem
- Compared to optimized LegUp configurations for the target FPGA

Improvements

- 10% improvement on weighted average
- 2 and 5 times improvements for some metrics and scenarios

Implementation in OpenTuner

- Ensemble with Simulated Annealing, Genetic Algorithms, and Nelder-Mead

Performance: darker blues are better

	WNS	*LUTs*	*Pins*	*BRAM*	*Regs*	*Blocks*	*Cycles*	*DSP*	*FMax*
aes	0.82	0.75	1.00	1.00	0.92	1.00	1.05	1.00	0.63
adpcm	0.84	0.94	1.17	1.00	0.96	1.00	0.94	0.69	0.74
sha	0.92	1.00	1.06	1.00	0.92	1.00	0.88	1.00	0.96
motion	0.99	1.00	1.00	1.00	1.01	1.00	1.00	1.00	0.98
mips	0.90	1.00	1.06	1.00	0.93	1.00	1.03	0.83	0.80
gsm	0.95	0.92	1.00	1.00	0.95	1.00	0.90	1.00	1.02
dfsin	0.87	1.11	1.06	1.00	1.27	1.00	1.25	0.53	0.56
dfmul	0.77	1.00	1.17	0.83	0.85	0.83	1.04	0.21	0.70
dfdiv	0.81	1.00	1.06	1.00	1.03	1.00	1.25	0.50	0.59
dfadd	0.97	1.00	1.00	1.00	0.97	1.00	1.00	1.00	0.94
blowfish	0.94	1.00	1.00	1.00	0.98	1.00	0.91	1.00	0.95

Weighted Average for all Scenarios

	Balanced	*Area*	*Performance*	*Perf. & Lat.*
aes	0.94	0.96	0.82	0.83
adpcm	0.84	0.83	0.84	0.76
sha	0.98	0.96	0.92	0.88
motion	0.98	0.97	0.99	0.98
mips	0.95	0.91	0.90	0.95
gsm	0.95	0.89	0.95	0.92
dfsin	0.93	0.94	0.87	0.97
dfmul	0.85	0.82	0.77	0.86
dfdiv	0.84	0.77	0.81	0.82
dfadd	1.00	0.99	0.97	0.98
blowfish	0.99	0.99	0.94	0.96
Average	0.93	0.91	0.89	0.90

Discussion

Autotuning with Heuristics

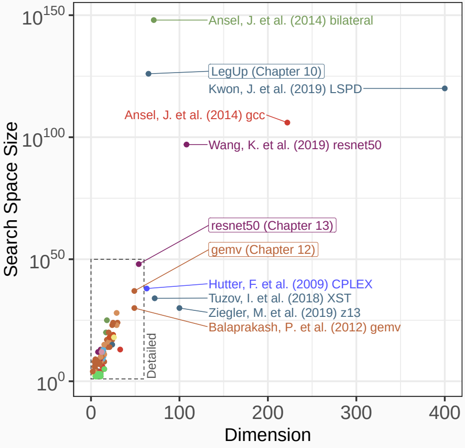
- Lack of structured exploration prevented statistical analyses and interpretation

Needle in a Haystack

- Global optimum in 10^{123} configurations?
- Are there better configurations to find?
- For how long should we continue exploring?

Proprietary Software Stack for FPGAs

- LegUp is now proprietary software



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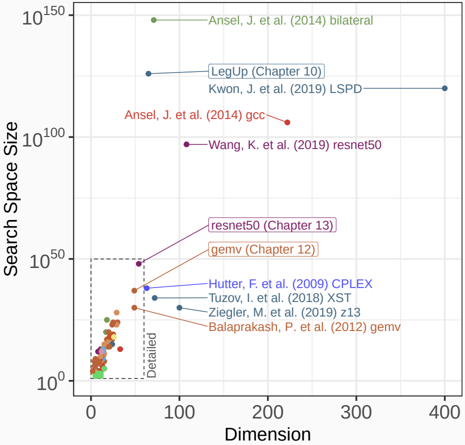


Sequential Design of Experiments

Structure explorations using modeling hypotheses to guide sampling and optimization

Backup: Applying Sequential Design of Experiments

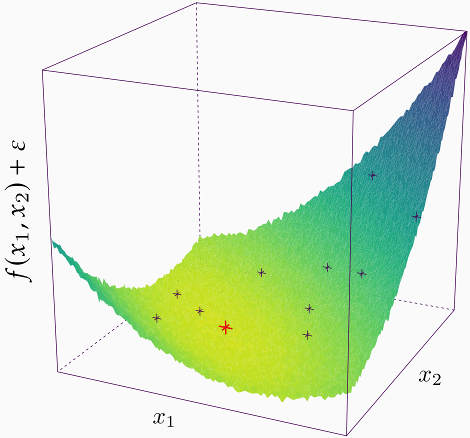
Search Space Hypotheses with Linear Models

Learning: Building Surrogates

- $f : \mathcal{X} \rightarrow \mathbb{R}$
- Model: $f(\mathbf{x}) = \mathbf{x}^\intercal \boldsymbol{\theta} + \varepsilon$, with $\varepsilon \sim \mathcal{N}(0, \sigma^2)$
- Data: $(\mathbf{x}_k, y_k = f(\mathbf{x}_k))$
- $\mathbf{x}_{1,\ldots,n}$ in a given design $\mathbf{X}$

10 Measurements of Booth's Function

$$f(\mathbf{x}) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2 + \varepsilon$$



Search Space Hypotheses with Linear Models

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- $f : \mathcal{X} \to \mathbb{R}$
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Minimize a Surrogate instead of f

- Surrogate: $\hat{f}_\theta(\mathbf{x}') = \mathbf{x}'^\mathsf{T}\hat{\boldsymbol{\theta}}$
- Estimator: $\hat{\boldsymbol{\theta}} = (\mathbf{X}^\mathsf{T}\mathbf{X})^{-1}\mathbf{X}^\mathsf{T}\mathbf{y}$

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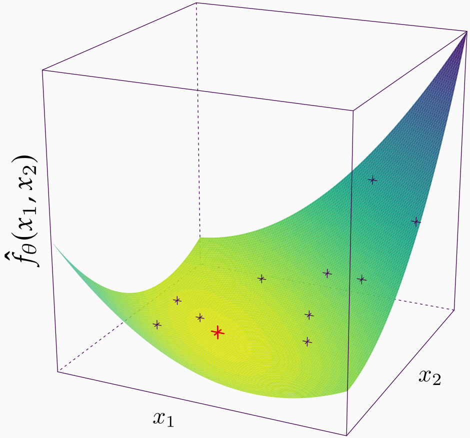
$$\hat{f}_\theta(\mathbf{x}) = \hat{\theta}_0 + \hat{\theta}_1 x_1 + \hat{\theta}_2 x_2 + \hat{\theta}_3 x_1^2 + \hat{\theta}_4 x_2^2 + \hat{\theta}_5 x_1 x_2$$



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Variance of $\hat{\theta}$ is independent of $\mathbf{y}$

$$\mathrm{Var}(\hat{\boldsymbol{\theta}}) = (\mathbf{X}^\mathsf{T}\mathbf{X})^{-1}\sigma^2$$

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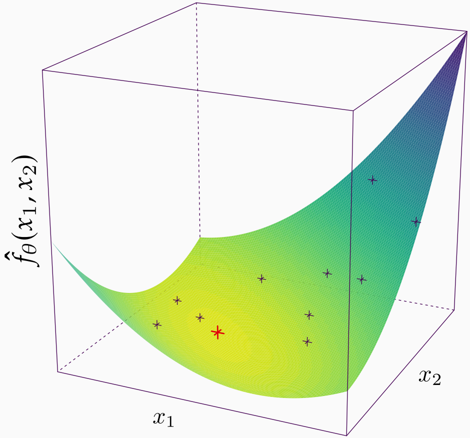


Design of Experiments

Choosing the Design $\mathbf{X}$

- Minimizes Var($\hat{\theta}$)
- Decreases number of experiments in $\mathbf{X}$
- Enables testing hypotheses

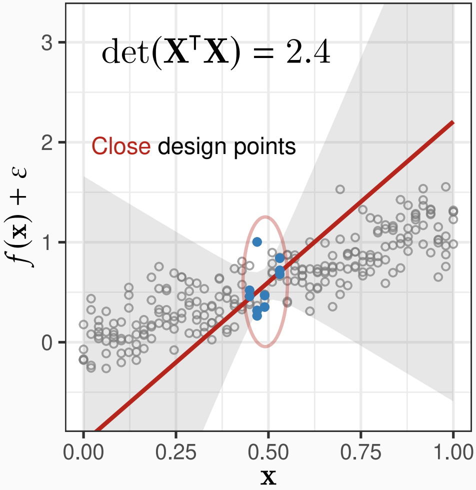
Components

- $\mathbf{X}_{n \times p}$: design matrix
- $\mathbf{x}_{1 \times n} \in \mathbf{X}$: factor columns
- $x_1, \ldots, x_p \in \mathbf{x}$: chosen factor levels

Examples

- Factorial designs, screening, Latin Hypercube and low-discrepancy sampling, optimal design

Distance of Experiments Impacts Var($\hat{\theta}$)



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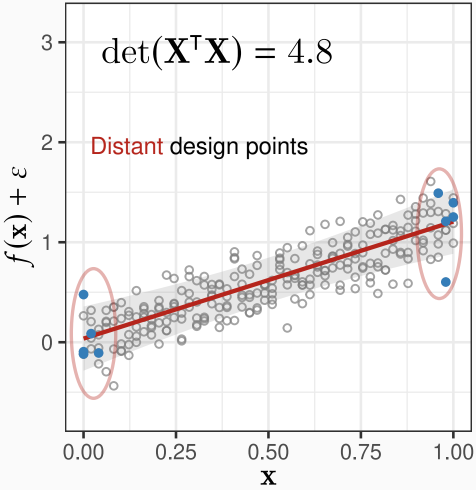

Optimal Design: Parsimony

Sampling with Different Models

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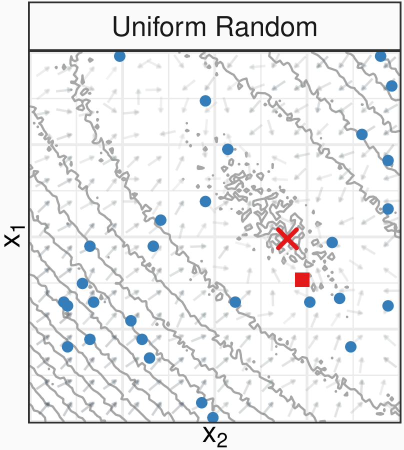
Designs

- Building surrogates within a constrained budget
- Exploiting known search space structure
- Testing modeling hypotheses

Maximizing det$(\mathbf{X}^\mathsf{T}\mathbf{X})$ by Swapping Rows

- Requires an initial **model**
- Choose best rows for $\mathbf{X}$ from a large set
- $\mathrm{D}(\mathbf{X}) \propto \det(\mathbf{X}^\mathsf{T}\mathbf{X})$



×: global optimum, ■: best point found, •: measurements

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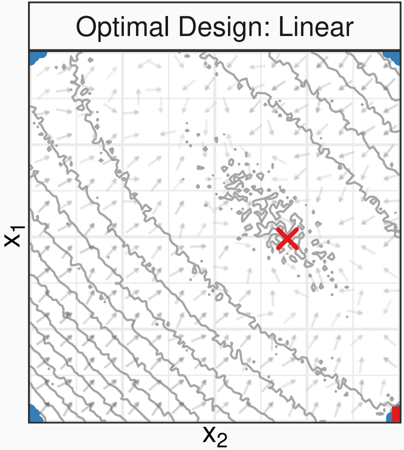

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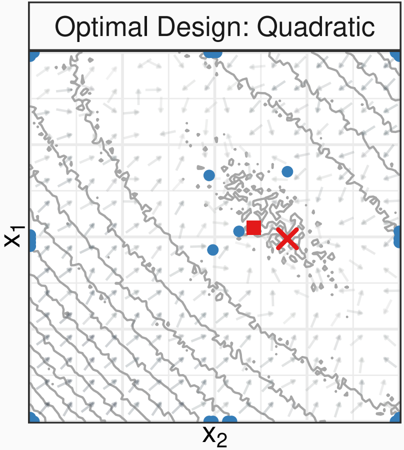

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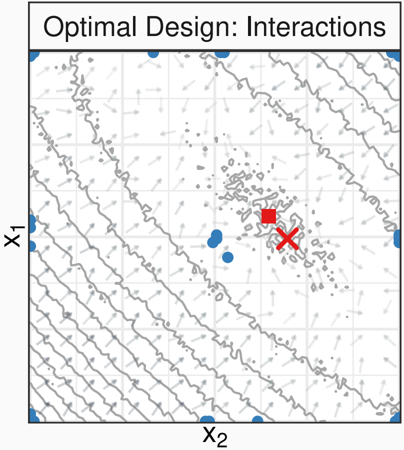

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Optimal Design: Parsimony

Sampling with Different Models

$$\hat{f}_\theta(\mathbf{x}) = \hat{\theta}_0 + \hat{\theta}_1 x_1 + \hat{\theta}_2 x_2 + \hat{\theta}_3 x_1^2 + \hat{\theta}_4 x_2^2 + \hat{\theta}_5 x_1 x_2$$

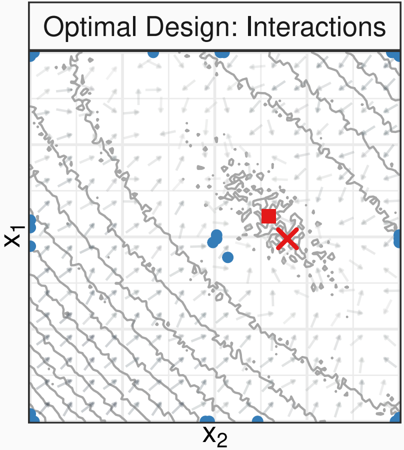
Designs

- Building surrogates within a constrained budget
- Exploiting known search space structure
- Testing modeling hypotheses

Maximizing $\det(\mathrm{X}^\intercal \mathrm{X})$ by Swapping Rows

- Requires an initial **model**
- Choose best rows for $\mathbf{X}$ from a large set
- $\mathrm{D}(\mathbf{X}) \propto \det(\mathbf{X}^\intercal \mathbf{X})$

Best design is independent of measurements



×: global optimum, ■: best point found,
●: measurements

Interpreting Significance with Analysis of Variance

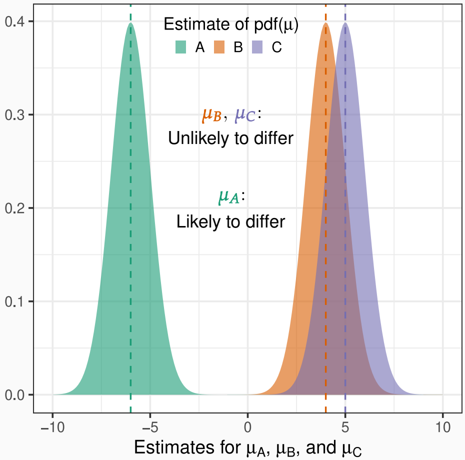
Analysis of Variance (ANOVA)

- Identify which factors and levels are significant

Steps

- Group observations by factor and factor levels
- Estimate distributions for each group mean μ
- Run F-tests for significance of differences between means

One-Way ANOVA for Levels A, B, C



Interpreting Significance with Analysis of Variance

Analysis of Variance (ANOVA)

- Identify which factors and levels are significant

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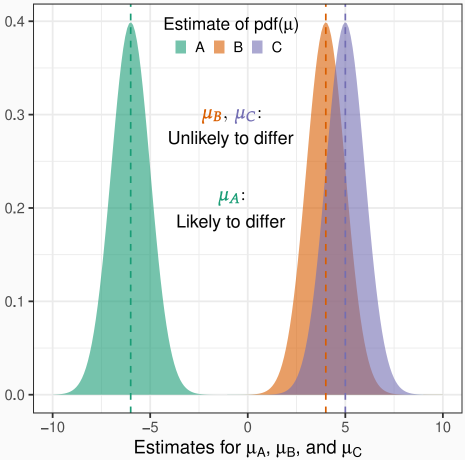
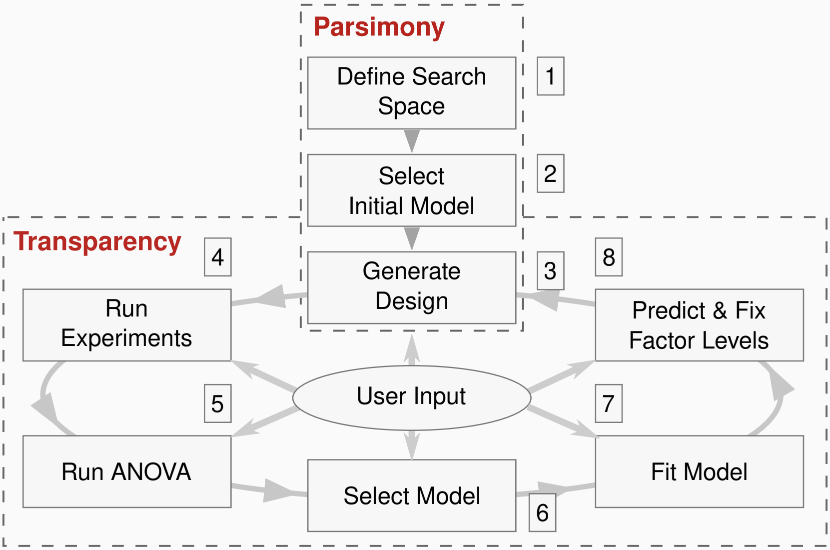
Enables refining initial hypotheses

One-Way ANOVA for Levels A, B, C



A Transparent and Parsimonious Approach to Autotuning



Application: OpenCL GPU Laplacian Kernel

Edge Detection with the Laplacian

The OpenCL Kernel

- Highly optimized
- Efficiently parametrized
- Generated by BOAST
- Completely evaluated previously

Search Space with 10^4 Valid Configurations

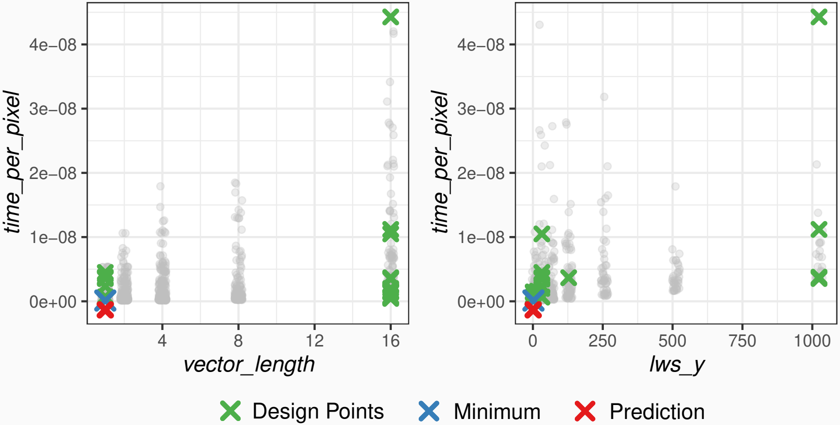
Factor	Levels	Short Description
vector_length	$2^0, \ldots, 2^4$	Size of vectors
load_overlap	*true*, *false*	Load overlaps in vectorization
temporary_size	$2, 4$	Byte size of temporary data
elements_number	$1, \ldots, 24$	Size of equal data splits
y_component_number	$1, \ldots, 6$	Loop tile size
threads_number	$2^5, \ldots, 2^{10}$	Size of thread groups
lws_y	$2^0, \ldots, 2^{10}$	Block size in y dimension

Performance Metric and Starting Model

$$\begin{aligned} \textit{time\_per\_pixel} \sim\ & \textit{y\_component\_number} + \frac{1}{\textit{y\_component\_number}} + \\ & \textit{temporary\_size} + \textit{vector\_length} + \textit{load\_overlap} + \\ & \textit{lws\_y} + \frac{1}{\textit{lws\_y}} + \textit{elements\_number} + \frac{1}{\textit{elements\_number}} + \\ & \textit{threads\_number} + \frac{1}{\textit{threads\_number}} \end{aligned}$$

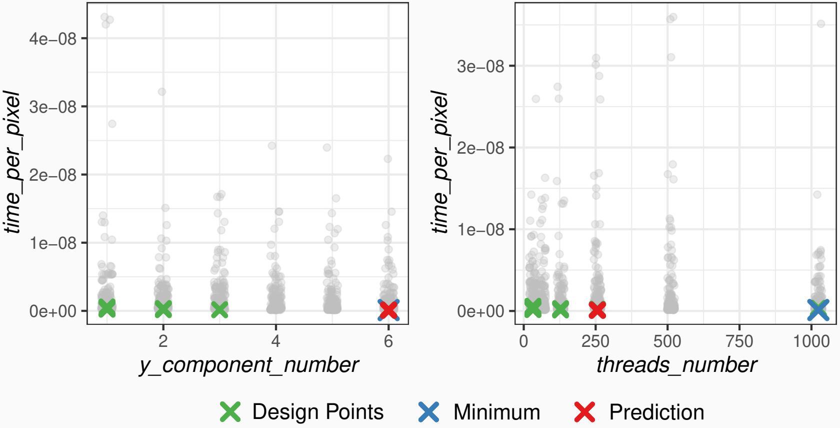
Sequential Approach to Optimization: Refining the Model

Step 1 Fix ***vector*** and ***lws_y***



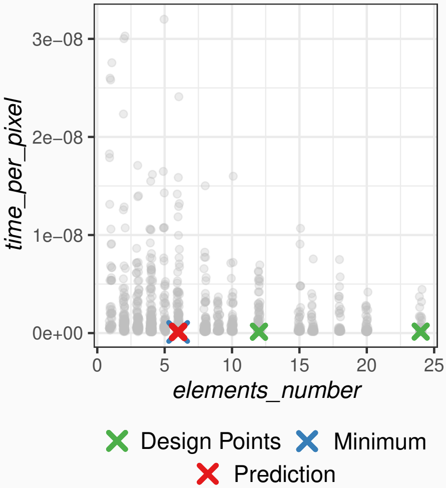
Sequential Approach to Optimization: Refining the Model

Step 2 Fix *y_cmp.* and *threads*



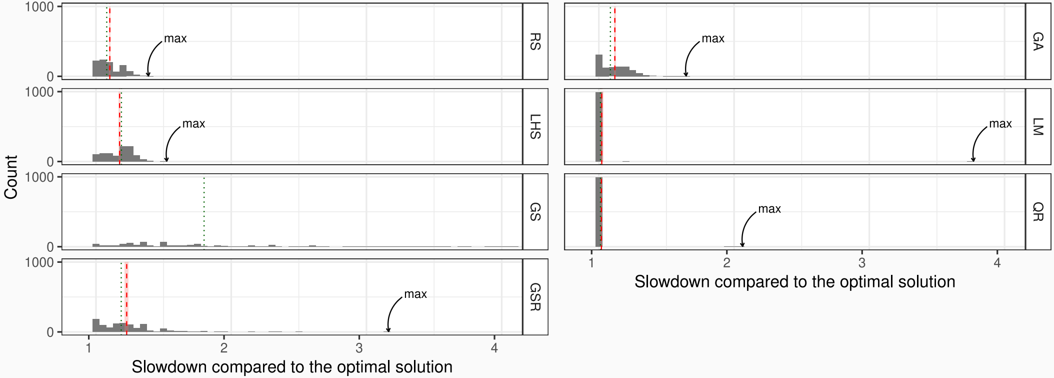
Sequential Approach to Optimization: Transparency

Step 3 Fix *elements*



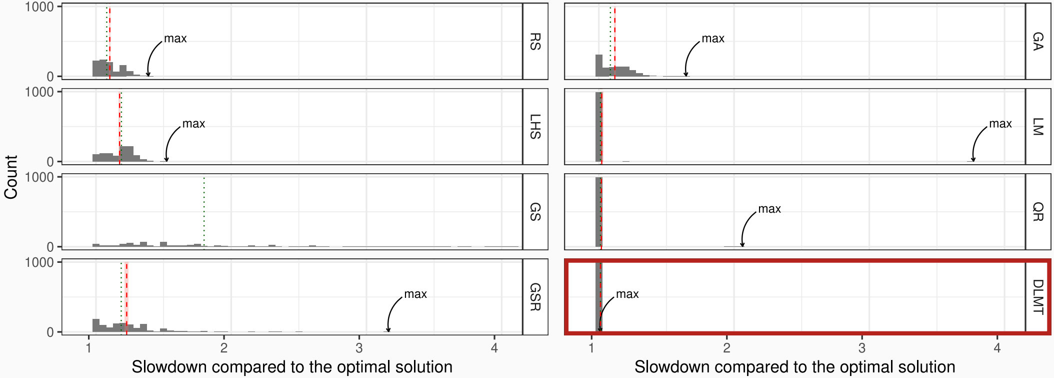
Step	Term	Sum Sq.	F-value	p(>F)
1^{st}	*y_component_number*	2.1×10^{-18}	7.3×10^{-1}	4.1×10^{-1}
	1/y_component_number	4.4×10^{-18}	1.6×10^{0}	2.4×10^{-1}
	vector_length	1.3×10^{-17}	4.4×10^{0}	4.7×10^{-2}
	lws_y	6.9×10^{-17}	2.4×10^{1}	3.5×10^{-4}
	1/lws_y	1.8×10^{-17}	6.2×10^{0}	2.8×10^{-2}
	load_overlap	9.1×10^{-20}	3.2×10^{-2}	8.6×10^{-1}
	temporary_size	7.1×10^{-18}	2.5×10^{0}	1.4×10^{-1}
	elements_number	3.1×10^{-19}	1.1×10^{-1}	7.5×10^{-1}
	1/elements_number	1.3×10^{-18}	4.4×10^{-1}	5.2×10^{-1}
	threads_number	7.2×10^{-18}	2.5×10^{0}	1.4×10^{-1}
	1/threads_number	4.3×10^{-18}	1.5×10^{0}	2.4×10^{-1}
2^{nd}	*y_component_number*	1.2×10^{-19}	2.1×10^{1}	1.4×10^{-3}
	1/y_component_number	1.4×10^{-20}	2.4×10^{0}	1.5×10^{-1}
	load_overlap	4.1×10^{-21}	7.3×10^{-1}	4.1×10^{-1}
	temporary_size	1.4×10^{-21}	2.6×10^{-1}	6.2×10^{-1}
	elements_number	6.0×10^{-22}	1.1×10^{-1}	7.5×10^{-1}
	1/elements_number	2.7×10^{-21}	4.8×10^{-1}	5.0×10^{-1}
	threads_number	7.2×10^{-21}	1.3×10^{0}	2.9×10^{-1}
	1/threads_number	2.9×10^{-20}	5.1×10^{0}	4.0×10^{-2}
3^{rd}	*load_overlap*	7.4×10^{-25}	3.8×10^{0}	1.1×10^{-1}
	temporary_size	1.1×10^{-22}	5.7×10^{2}	2.4×10^{-1}
	elements_number	9.3×10^{-22}	4.7×10^{3}	1.2×10^{-8}
	1/elements_number	3.1×10^{-22}	1.6×10^{3}	1.9×10^{-7}

Results: 1000 Repetitions with a Budget of 120 Measurements



RS: Random Sampling, LHS: Latin Hypercube Sampling, GS: Greedy Search,
GSR: Greedy Search w. Restart, GA: Genetic Algorithm, LM: Linear Model, QR: Quantile Regression

Results: 1000 Repetitions with a Budget of 120 Measurements



RS: Random Sampling, LHS: Latin Hypercube Sampling, GS: Greedy Search,
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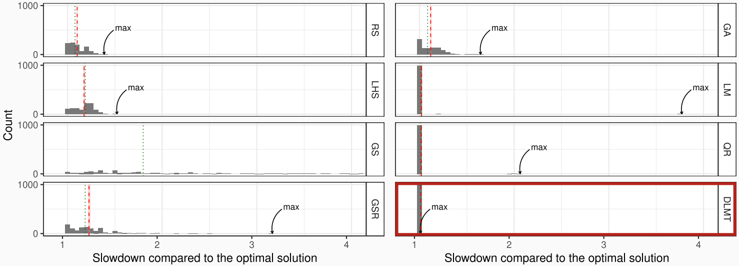
DLMT: D-Optimal Designs, Linear Model w. Transform

Parsimony under Tight Budget Constraints



	Slowdown			Budget	
Method	*Mean*	*Min.*	*Max.*	*Mean*	*Max.*
Random Sampling (RS)	1.10	1.00	1.39	120.00	120
Latin Hypercube Sampling (LHS)	1.17	1.00	1.52	98.92	125
Greedy Search (GS)	6.46	1.00	124.76	22.17	106
Greedy Search w. Restart (GSR)	1.23	1.00	3.16	120.00	120
Genetic Algorithm (GA)	1.12	1.00	1.65	120.00	120
Linear Model (LM)	1.02	1.01	3.77	119.00	119
Quantile Regression (QR)	1.02	1.01	2.06	119.00	119
D-Opt., Linear Model w. Transform (DLMT)	**1.01**	**1.01**	**1.01**	**54.84**	**56**

Application: Search Problems in Automatic Performance Tuning (SPAPT)

SPAPT Kernels

- 16 problems on multiple HPC domains
- Generated by ORIO
- Sets of constraints for each kernel
- Too large to completely evaluate
- Same starting model for all kernels

Numeric Parameters

- Unrolling, blocking, for multiple loops

Binary Categorical Parameters

- Parallelization, vectorization, scalar replacement

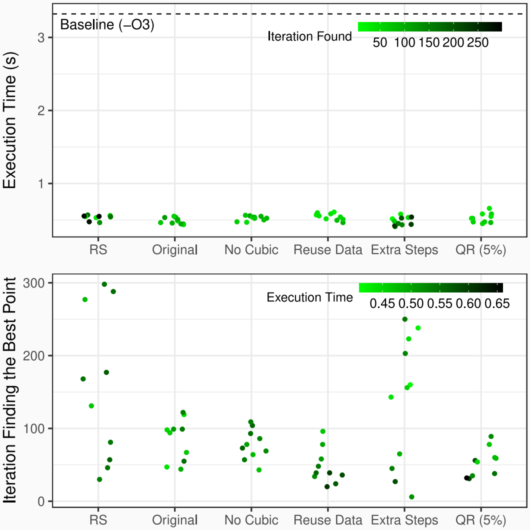
Search Spaces

Kernel	Short Description	Factors	Size
dgemv3	Scalar, vector & matrix mult.	49	10^{36}
stencil3d	3-D stencil computation	29	10^{27}
trmm	Triangular matrix operations	25	10^{23}
gemver	Vector mult. & matrix add.	24	10^{22}
tensor	Tensor matrix mult.	20	10^{19}
correlation	Correlation computation	21	10^{17}
atax	Matrix transp. & vector mult.	18	10^{16}
adi	Matrix sub., mult., & div.	20	10^{15}
seidel	Matrix factorization	15	10^{14}
mm	Matrix multiplication	13	10^{12}
lu	LU decomposition	14	10^{12}
bicg	Subkernel of BiCGStab	13	10^{11}
gesummv	Scalar, vector, & matrix mult.	11	10^{9}
mvt	Matrix vector product & transp.	12	10^{9}
jacobi	1-D Jacobi computation	11	10^{9}
hessian	Hessian computation	9	10^{7}

Performance Metric and Starting Model

$$\textit{run\_time} \sim \sum_{i=1,\dots,p} x_i + x_i^2 + x_i^3$$

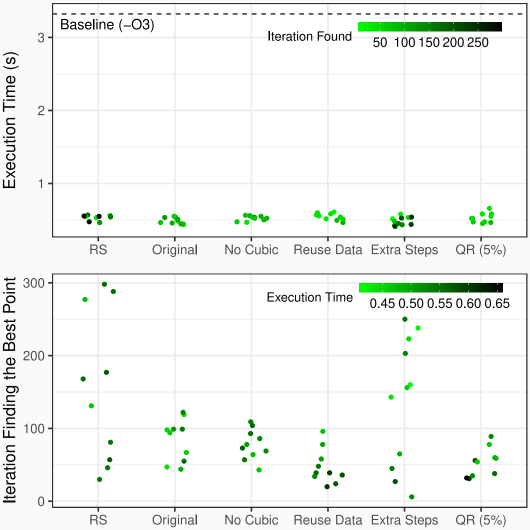
Summarizing Results: *bicg* Kernel



Interpreting the Optimization

- 4 steps, budget of 300 measurements
- Improvements compared to *-O3*, not so much compared to Random Sampling
- 2 most practically significant parameters detected at 1st and 2nd steps
- Other factors were statistically significant, but not practically

Summarizing Results: *bicg* Kernel



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Is there anything else to find?

- How far are we from the global optimum?

Applying Design of Experiments and Learning to Autotuning

Random Sampling has Good Performance

- Abundance of local optima?

Motivating Results with the Laplacian Kernel

- Knowledge of the search space
- Good starting model

Broader Evaluation with SPAPT Kernels

- Is there something else to find?
- Can we find it by exploiting structure?

Different Abstraction Levels

- Algorithm, implementation, dependencies, compiler, OS, hardware
- How to combine them effectively?

Sequential and Incremental Approach

- Definitive search space restrictions
- Experiments and improvements by batch
- Rigid models

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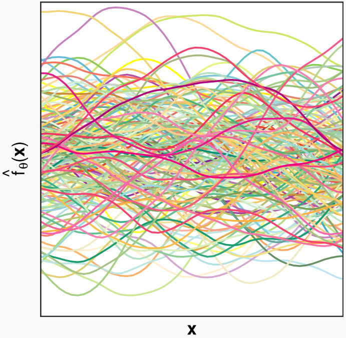
More Flexibility with Gaussian Processes

Balance exploitation of structure with unrestricted exploration

Backup: Applying Active Learning with Gaussian Processes

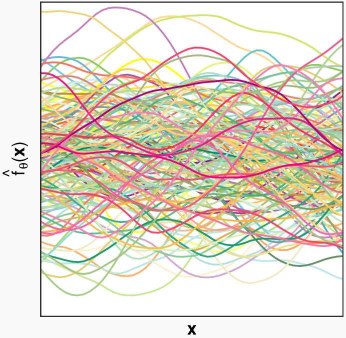
Sampling Functions with Gaussian Process Regression

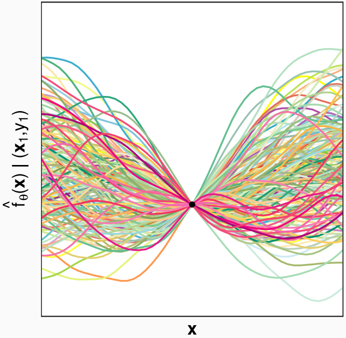


Gaussian Process Surrogates

- $f : \mathcal{X} \rightarrow \mathbb{R}$
- Model: $f(\mathbf{x}) \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$
- Data: $(\mathbf{x}_k, y_k = f(\mathbf{x}_k))$
- Surrogate $\hat{f}_\theta(\mathbf{x}) \sim f(\mathbf{x}) \mid \mathbf{X}, \mathbf{y}$

Sampling Functions with Gaussian Process Regression





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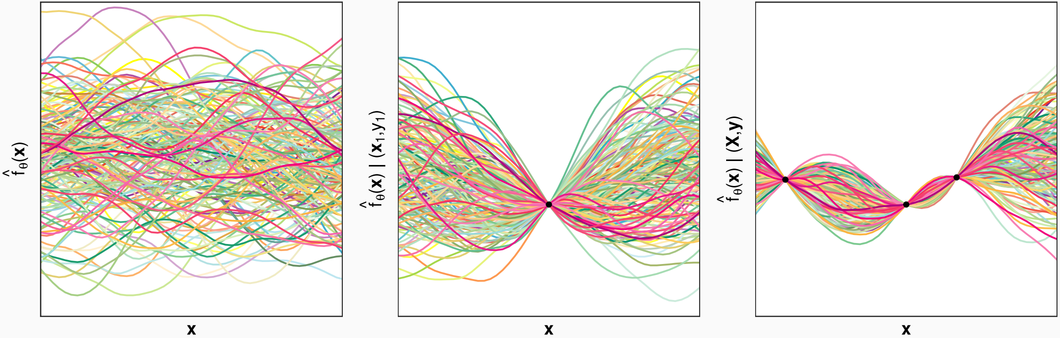

Gaussian Process Surrogates

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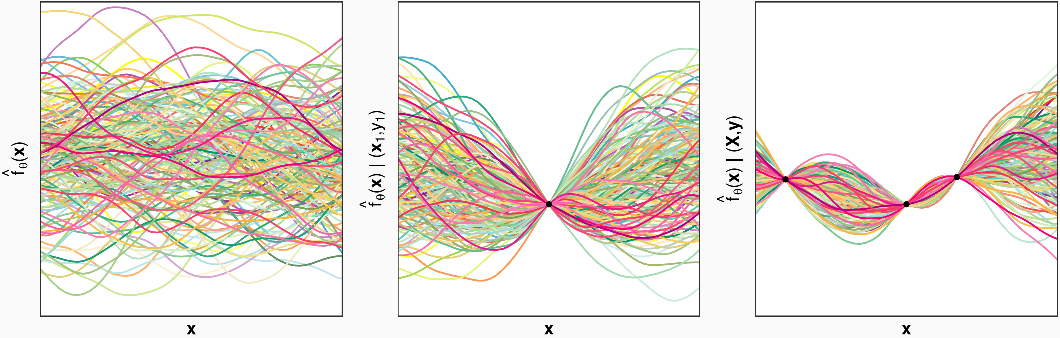

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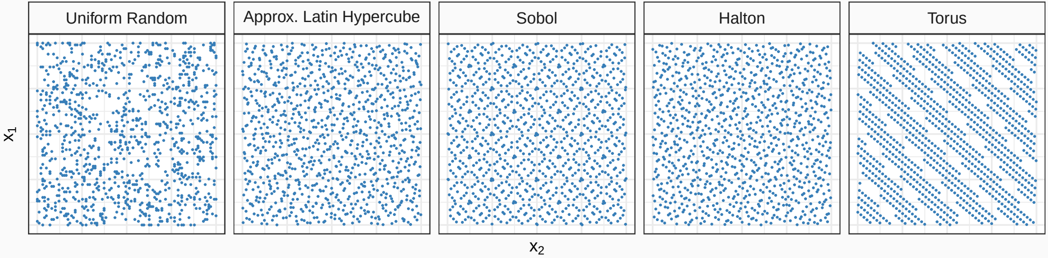
- Surrogate $\hat{f}_\theta(\mathbf{x}) \sim f(\mathbf{x}) \mid \mathbf{X}, \mathbf{y}$

How to choose X?

- Minimizing f
- Building an accurate surrogate
- Doing both?

Space-filling Designs: Sampling for High Dimension



Curse of Dimensionality: Sampling

- In high dimension, most sampled points are on the shell

Strategies

- Latin Hypercube Sampling: Partition and then sample, might need to optimize later
- Low-discrepancy: deterministic space-filling sequences

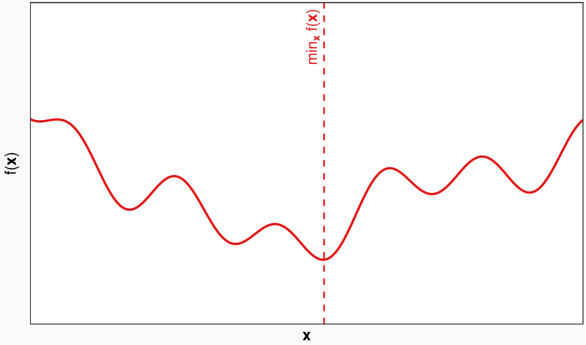
Optimization

- More uniform starting samples

Interpretation

- Sobol indices
- Still need many samples

Expected Improvement: Balancing Exploitation and Exploration



How to decide where to measure next?

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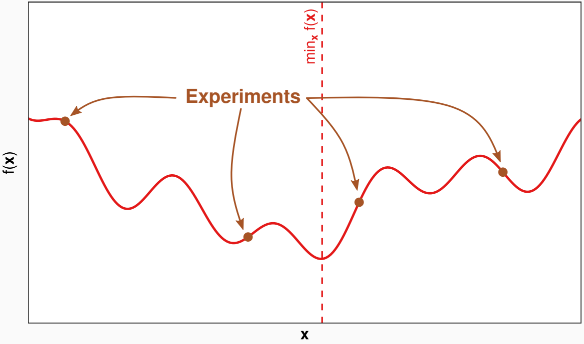

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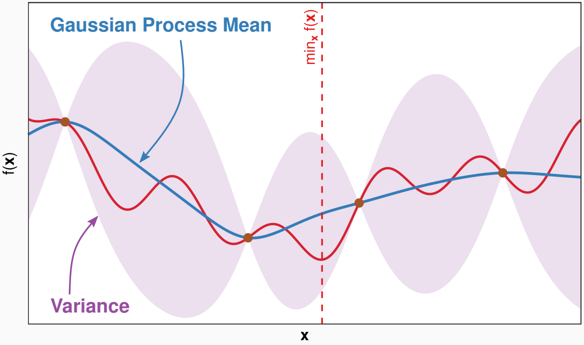

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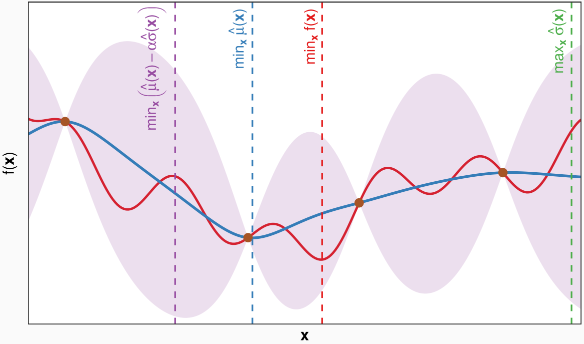

How to decide where to measure next?

- Explore: maximum **variance**
- Exploit: minimum **mean**
- Balance: minimum **mean** minus **confidence interval** lower bound

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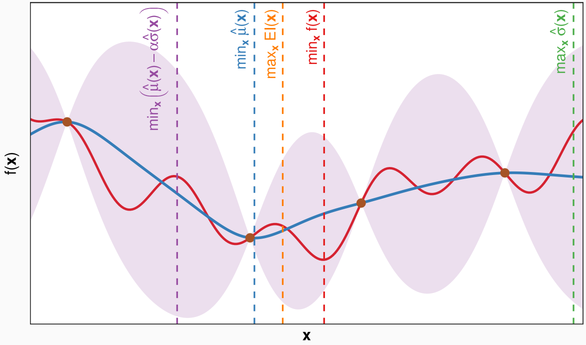


How to decide where to measure next?

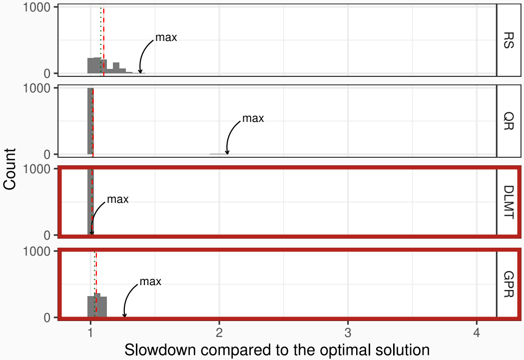
- Explore: maximum **variance**
- Exploit: minimum **mean**
- Balance: minimum **mean** minus **confidence interval** lower bound
- Balance: maximum **Expected Improvement**

Computing the Expected Improvement (EI)

$$\mathbb{E}[I(\mathrm{x})] = (y^* - \hat{\mu}(\mathrm{x}))\, \Phi\left(\frac{y^* - \hat{\mu}(\mathrm{x})}{\hat{\sigma}(\mathrm{x})}\right) + \hat{\sigma}(\mathrm{x})\, \phi\left(\frac{y^* - \hat{\mu}(\mathrm{x})}{\hat{\sigma}(\mathrm{x})}\right)$$

Application: OpenCL Laplacian and SPAPT Kernels

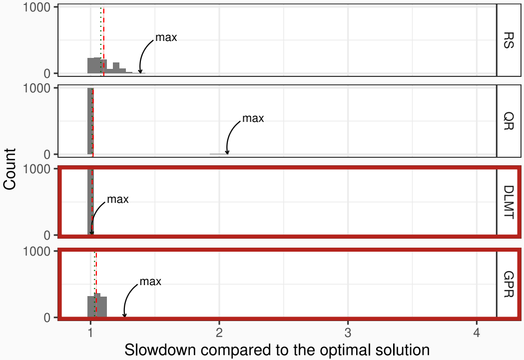
OpenCL Laplacian Kernel



- The more informed model performed better

Application: OpenCL Laplacian and SPAPT Kernels

OpenCL Laplacian Kernel



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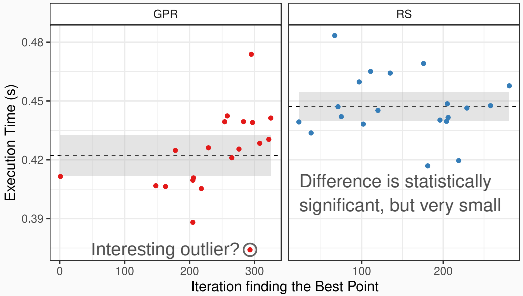
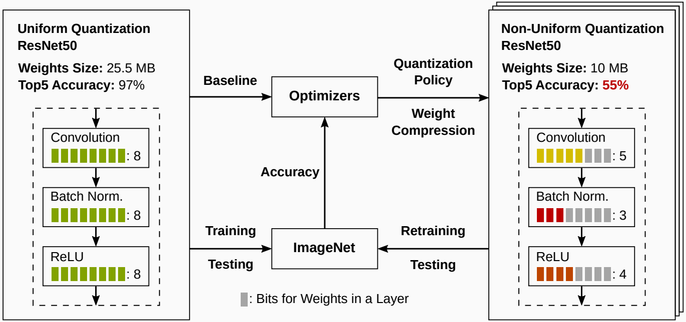
SPAPT *bicg* Kernel



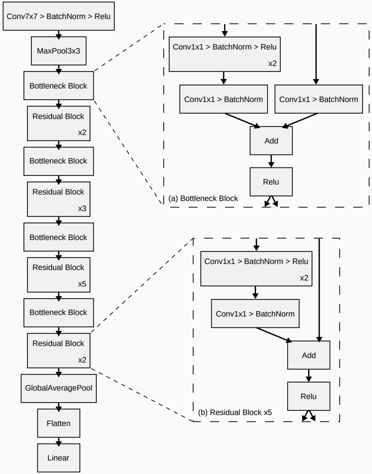
- Consistent, small improvements on RS
- Found outliers, but did not explore further

Application: Quantization for Convolutional Neural Networks

Keep Weights $\leq$ 10MB with Mixed-Precision Quantization



ResNet50: 10^{48} Configurations



Maintain Original Accuracy on ImageNet

Results

Accuracy Metrics

- Top1: correct class is the network's most probable prediction
- Top5: correct class is in the five most probable predictions

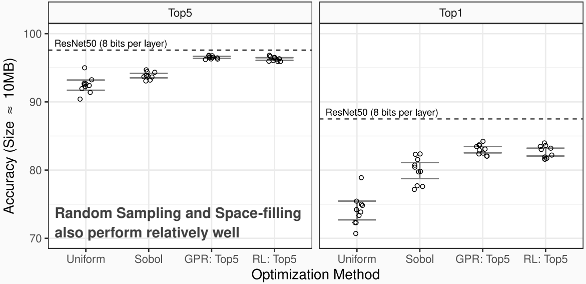
Constraints

- Weight size must be $\leq$ 10MB

Optimizing for Top5

- Compared with Random Sampling, Space-filling designs, and Reinforcement Learning
- GPR was more consistent

Comparison with Reinforcement Learning



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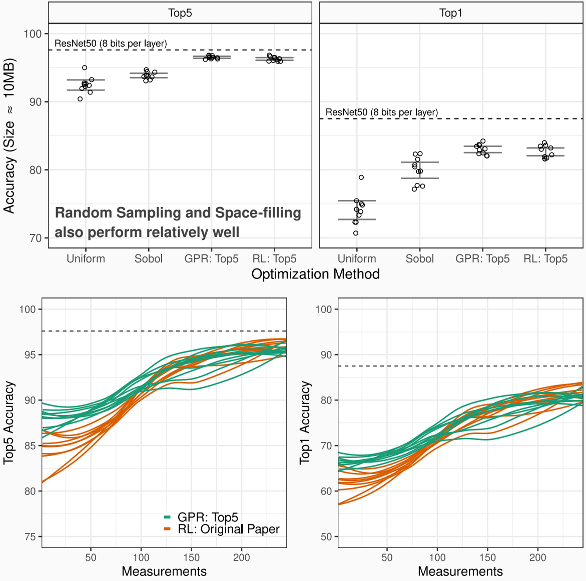
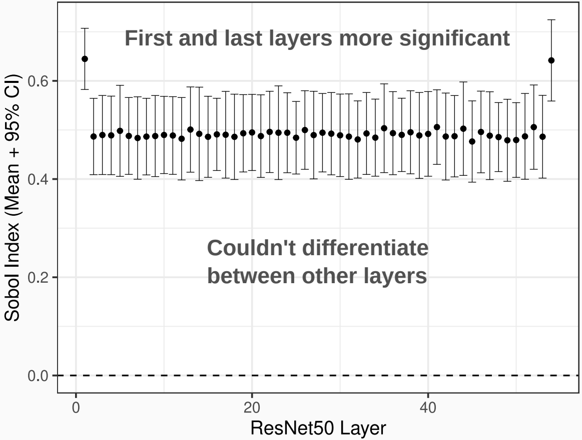


Interpreting Results

Computing Sobol Indices



- Using all data, and only Sobol samples: inconclusive

Optimizing for Size and Top5

- Adapted the RL algorithm
- GPR was more stable

Fitting a GP to All Data

- Enables leveraging entire dataset
- Extremely time-consuming
- Unclear if viable with RL

Expressing Structure with Kernels

- Could recover interpretability

Discussion

More Flexibility with Gaussian Processes

- No accurate modeling hypotheses needed
- Harder to interpret
- Not always achieves better optimizations
- Effort to build a good model can pay off

Online Learning

- Deciding where to measure at each new experiment
- Balancing exploitation and exploration
- No restriction to subspaces

Space-filling Designs

- Sampling in high dimension
- Filter to go around constraints

Context: Size of the Search Space