Towards multi-objective, region-based auto-tuning for parallel programs

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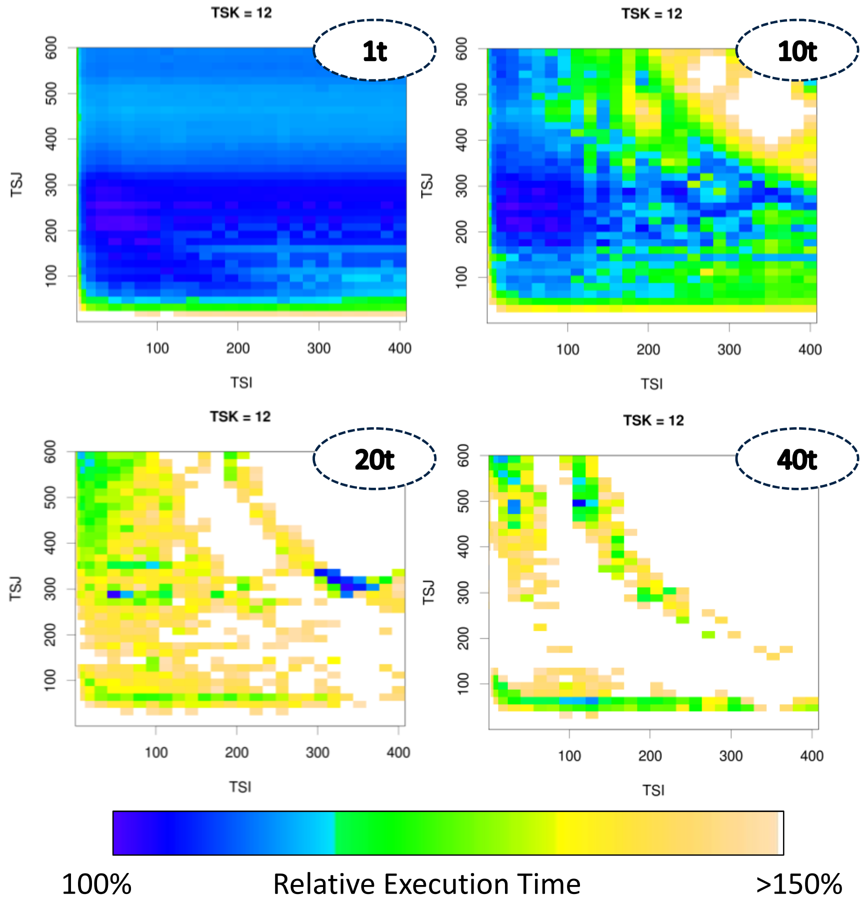
Why is it so hard to optimize codes for parallel systems?

- Question:
  - If the strategy for I/O scheduling, process scheduling, cache replacement policy would be changed, how would you re-write your code?
- Complexity, undecidability and difficulty to predict program and system behavior:
  - Dynamic re-allocation of cores and memory, clock speed, external load, sharing of resources, etc.
  - Operating system, external load, queuing systems, caches often difficult to predict

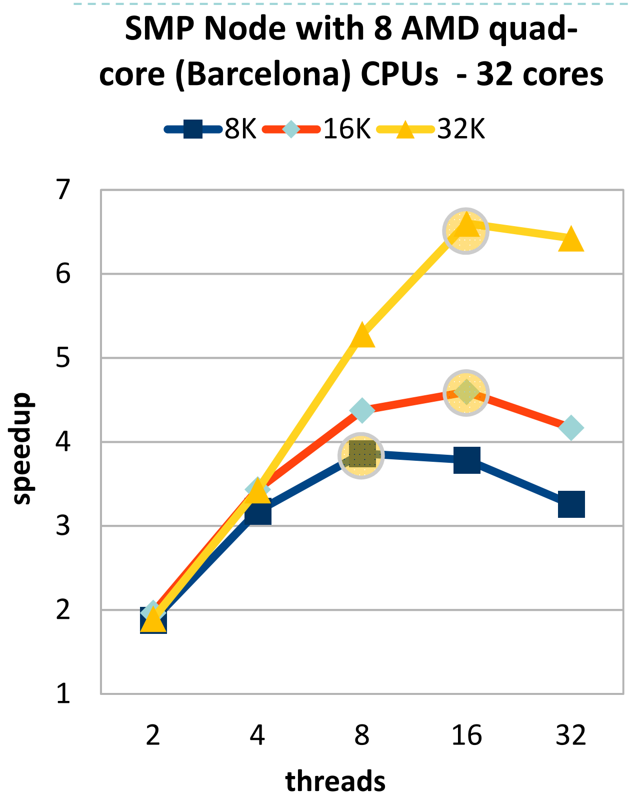
Modern processor and system architectures are so complex that it appears to be impossible “for a human being” to manually find best code transformation sequences for a program to optimize performance.

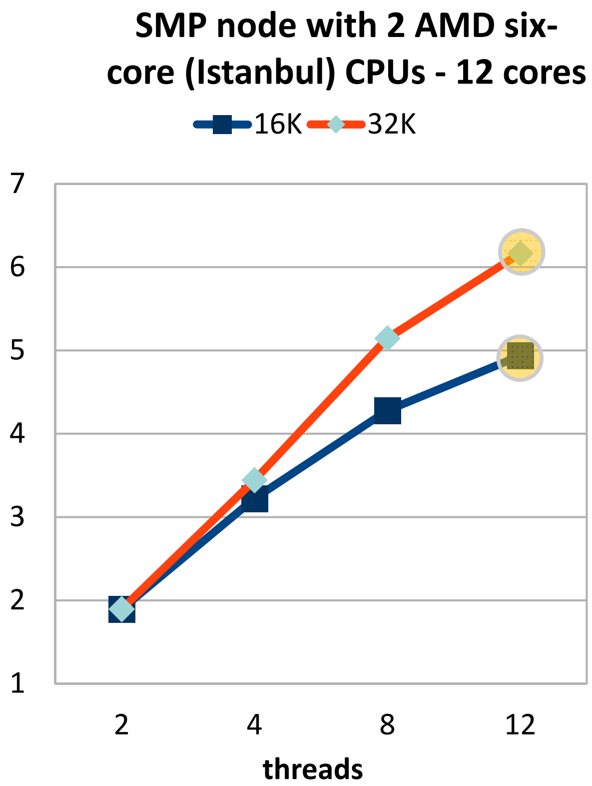
Impact of parallelism on tiling for matrix multiply relative execution time

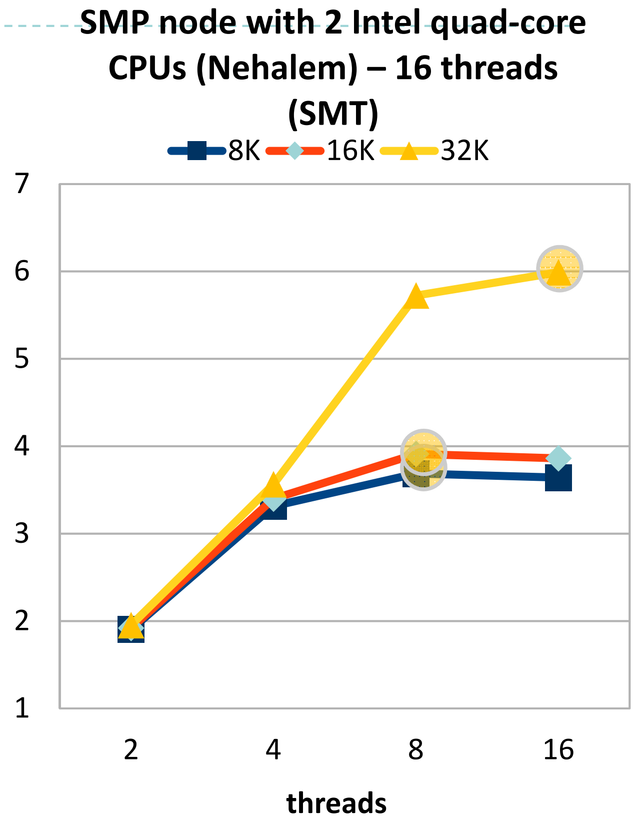
- MM-IJK loop order
  - 1400x1400
- Intel Westmere Arch.
  - 4 x 10 cores
  - 30MB L3 / Socket
- Brute Force Search
  - Tile Sizes I/J/K
  - # threads



ADI OpenMP Comparison







What is the optimal number of cores to use?

- Performance impact: CPU architecture, cache size and memory hierarchy
- Ideal number of threads requires knowledge about the program, architecture, and input data.

Search Space for Code Optimizations and Parallelization Strategies

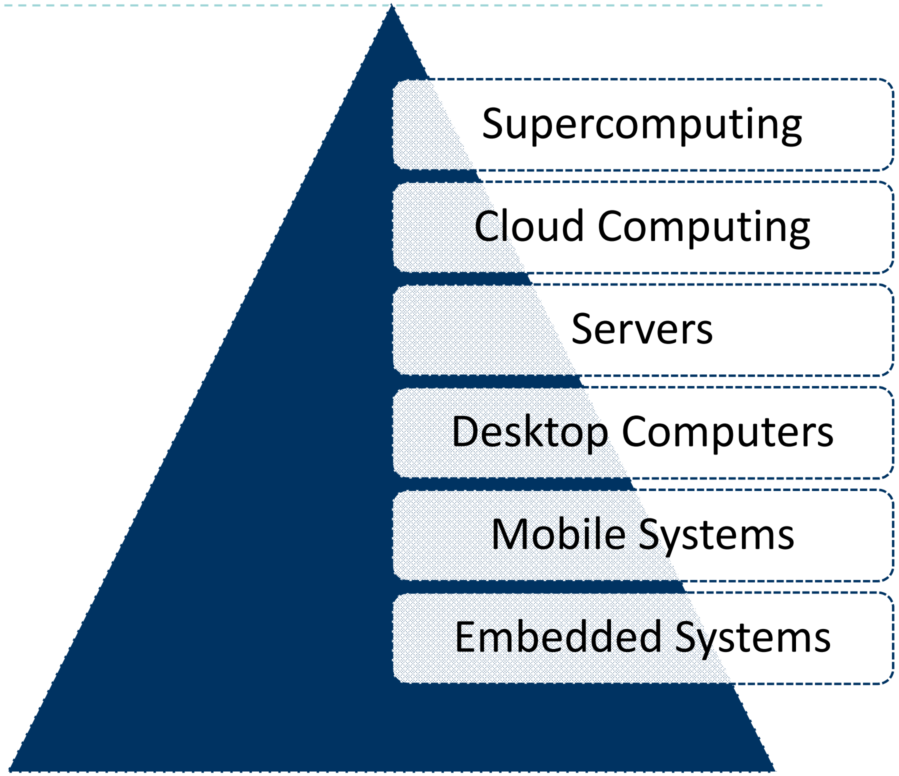
- code transformations
  - loop tiling, scheduling, data transpose, data distribution, …
- library settings
  - MPI has 100s of parameters
- target compiler flag setting
  - memory size, optimization flags, binary optimizations
- target machine configuration
  - nr. cores, frequency and power settings, turbo boost

Gigantic search space to explore for manual optimization.

➡ auto-tuning

Objectives for Optimization

- execution time
- memory footprint
- disc usage
- energy/power
- economic costs
- program size
- reliability
- security



- Auto-tuning for multiple objectives

Outline

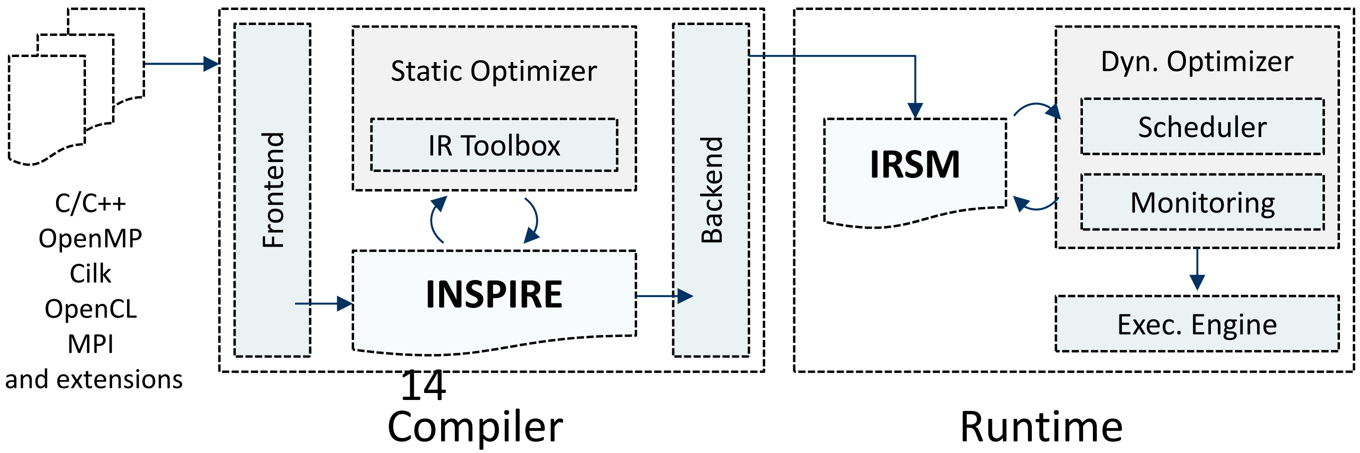
- Insieme Compiler Framework
- Multi-Objective Optimization and Auto-tuning
- Runtime / Efficiency / Energy
- Region-aware auto-tuning
- Experimental Results
- Conclusions

Insieme Compiler Framework

Insieme

Compiler and Runtime Research Platform

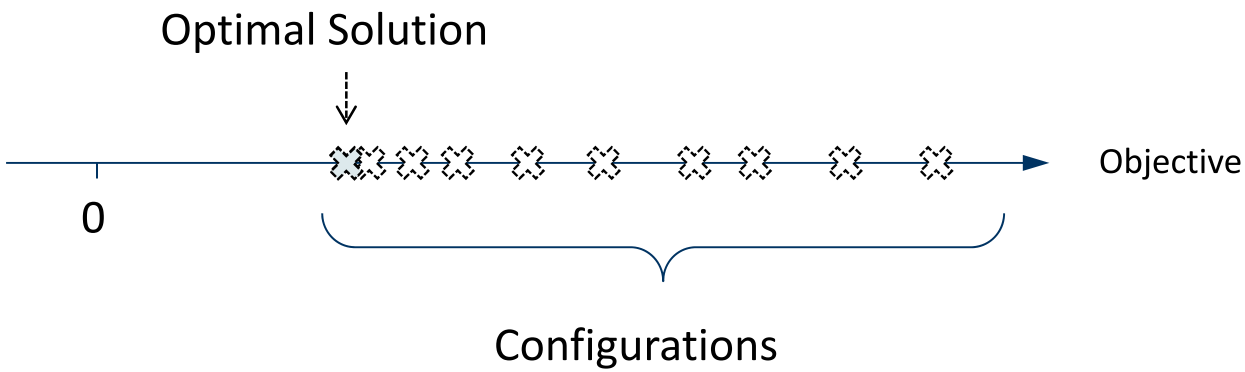
- *Insieme Compiler*
  - Source to Source Compiler for Parallel Codes
  - C/(C++) OpenMP, MPI, OpenCL, Cilk
  - Uniform Internal Representation (INSPIRE)
  - Analyses and Transformations Frameworks
    - e.g. Polyhedral Model or Pattern based
- *Insieme Runtime*
  - scheduling & runtime auto-tuning research
  - compiler-aided decision making processes
  - external load



Multi-Objective Optimization

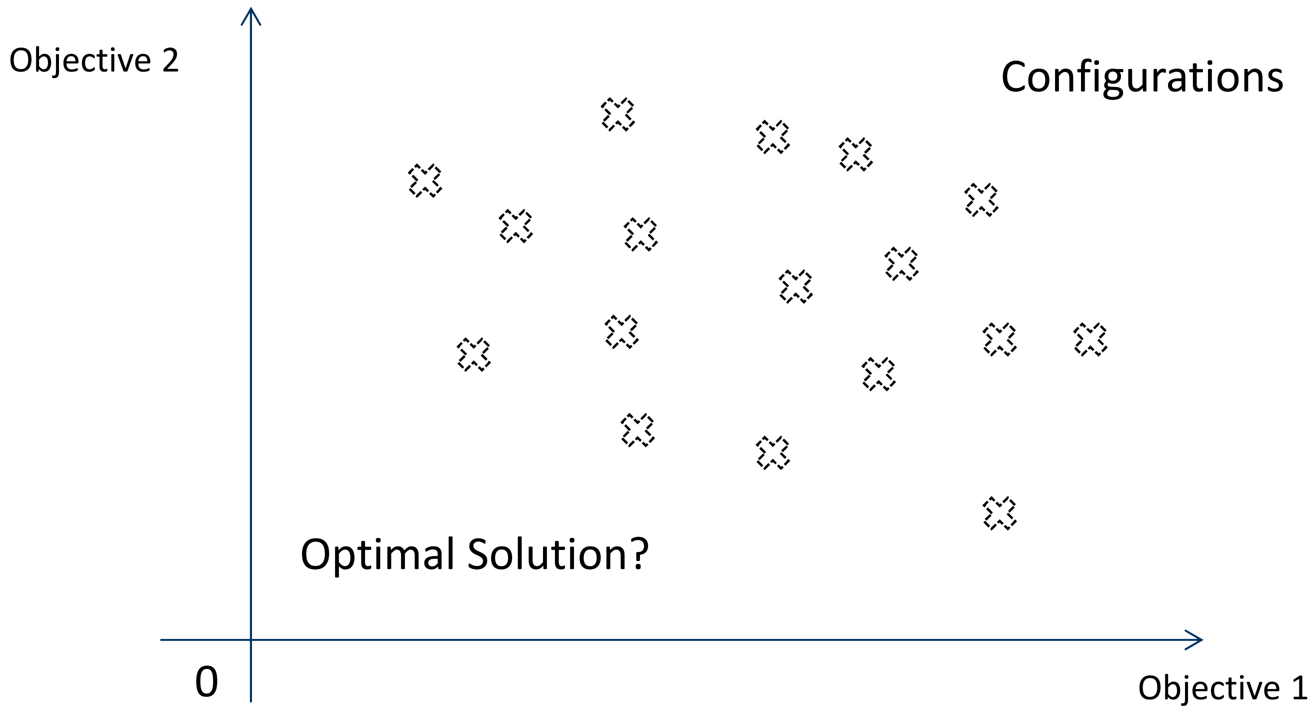
Mono-Objective Optimization

- configuration: specific code version with specific setting of tunable parameters



$$f : C \to \mathbb{R}$$

Multi-Objective Optimization

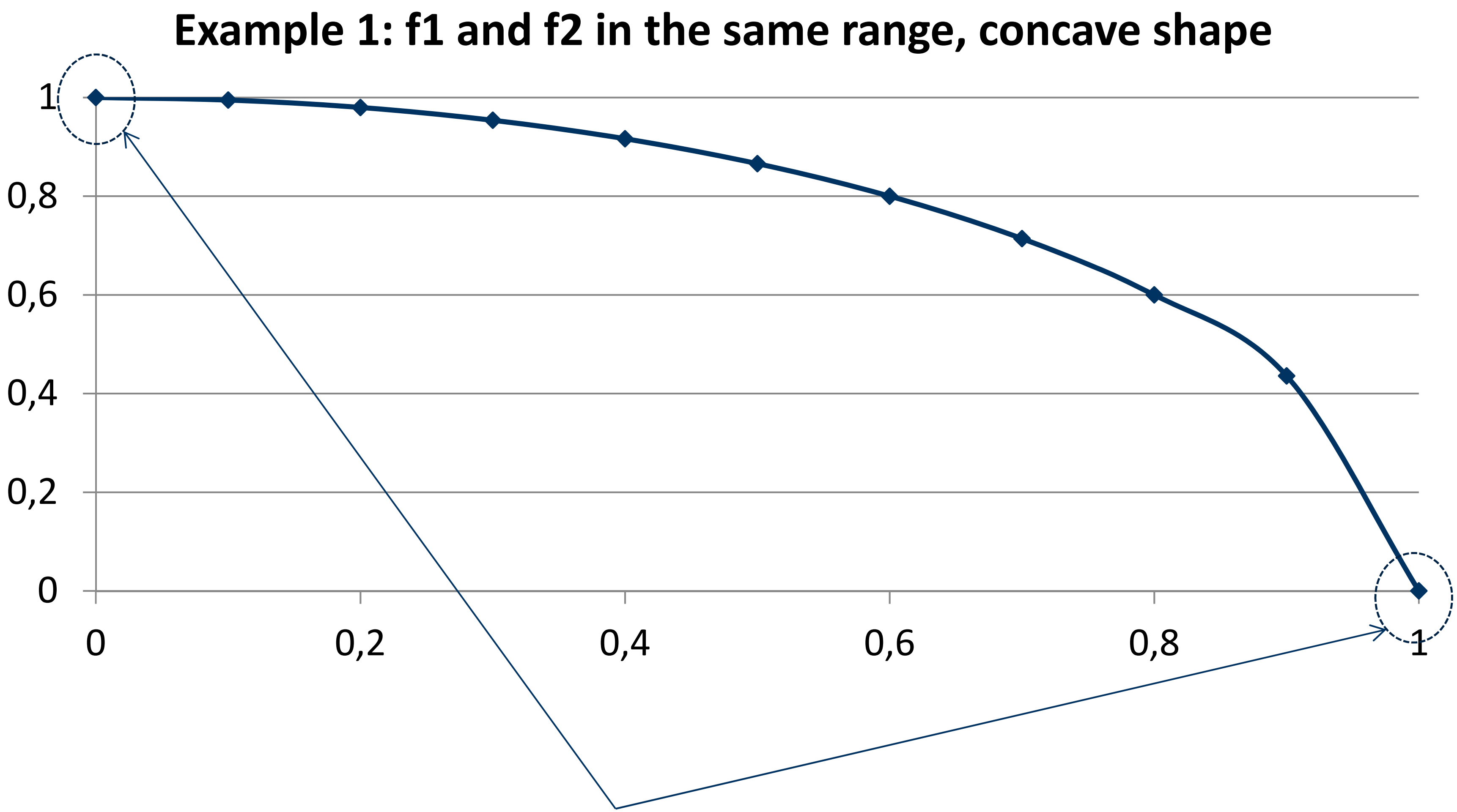


$$f: C \rightarrow \mathbb{R}^n$$

Multi-Objective Optimization with a single Function

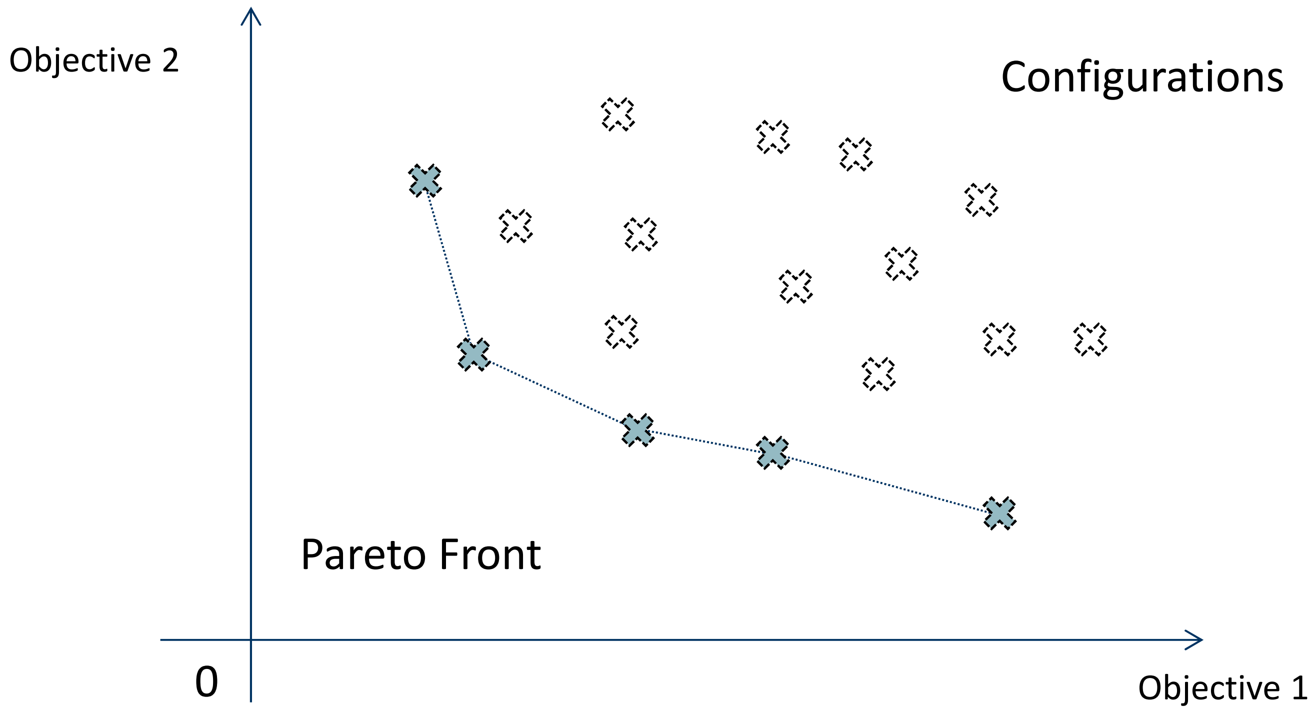
- Merge all objectives in a single function
  - Objectives are combined by means of weights (expressing user preferences)
  - Example:
    - Minimize energy consumption (f1) and runtime (f2) can be defined as minimizing the function
      - F = a * f1 + b * f2, where (a,b) are user preferences for that objective function
  - Drawbacks
    - F depends on the shape of the front and the value ranges of the objective functions
    - Therefore, there is no guarantee of obtaining the desired solution

Multi-Objective Optimization with a single Function



Two solutions are optimal for the preferences (0.5,0.5)
Which solution will be determined depends on the solver.

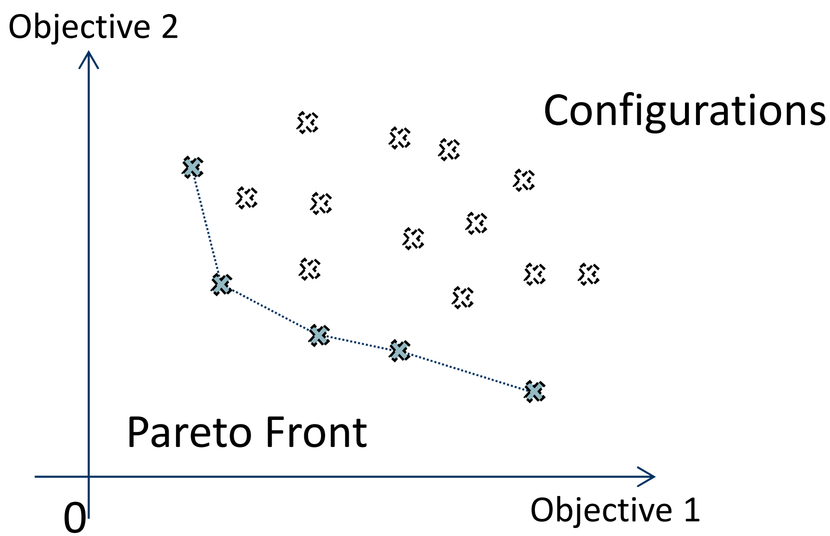
Multi-Objective Optimization with a Pareto Front



$$f: C \rightarrow \mathbb{R}^n$$

Multi-Objective Optimization with a Pareto Front

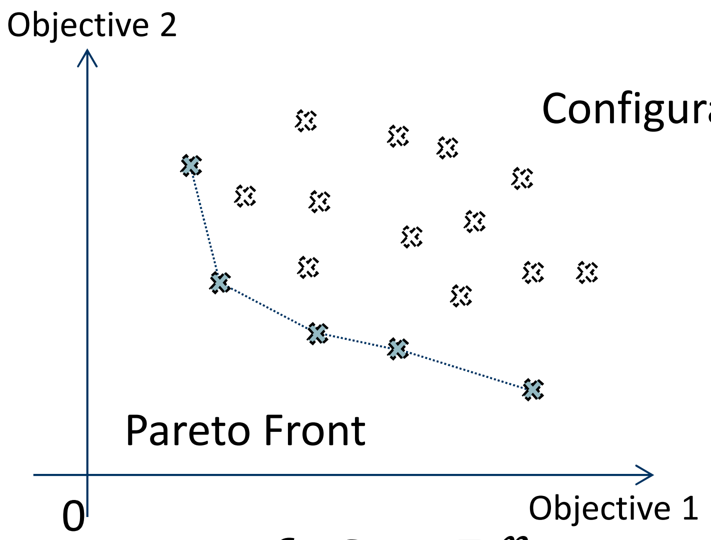
- Goals of Optimizer:
  - Push front toward ideal point
  - Evenly distributed points on front
  - Large number of points on front



$$f: C \to \mathbb{R}^n$$

Selection of a Solution

$$g(c) = \sum_{i=1}^{o} w_i \frac{f_i(c) - f_i^{\min}}{f_i^{\max} - f_i^{\min}}$$



$f : C \rightarrow \mathbb{R}^n$

Optimization Objectives

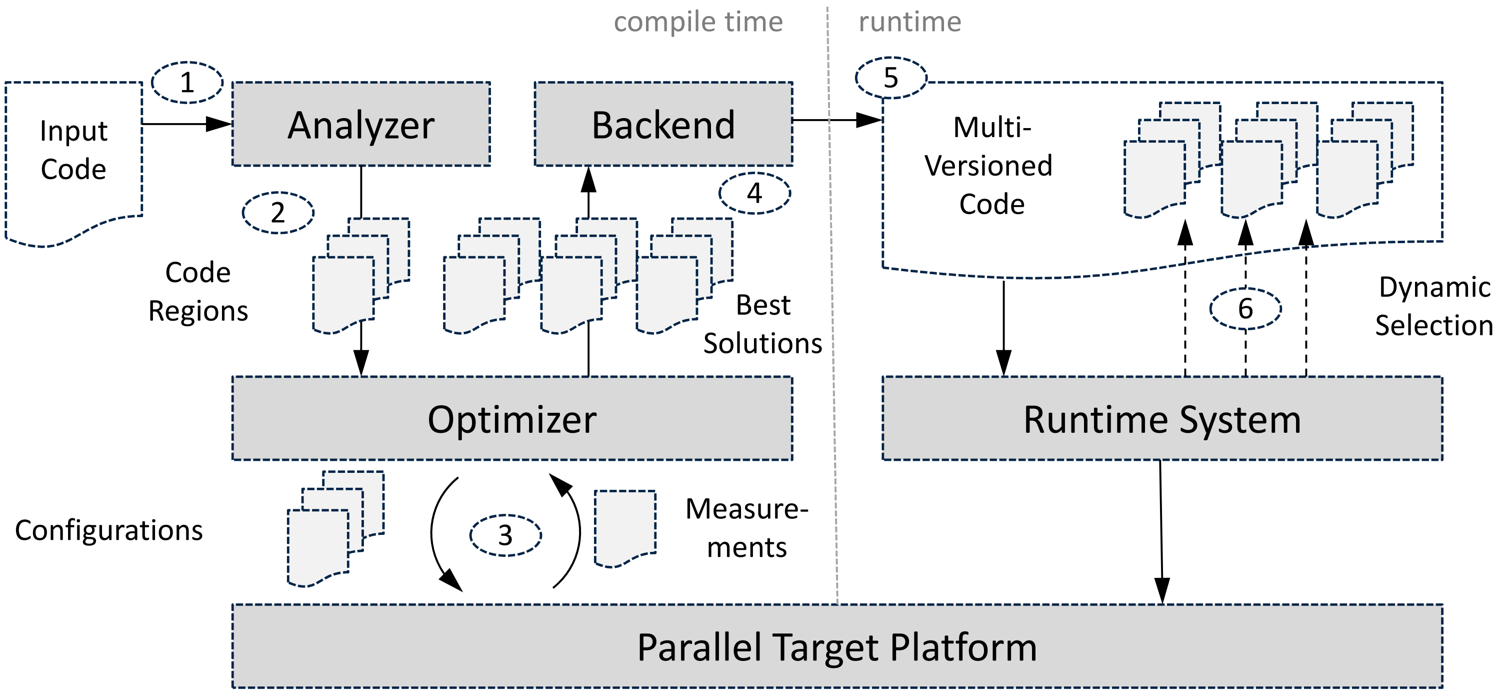
- Execution time
- Resource efficiency
- Energy consumption
- Memory footprint
- Economic costs
- …

Insieme can simultaneously handle an arbitrary number of measurable objectives.

Compiler Framework

Laying the Foundation

Insieme Multi-Objective Auto-Tuning Compiler Architecture



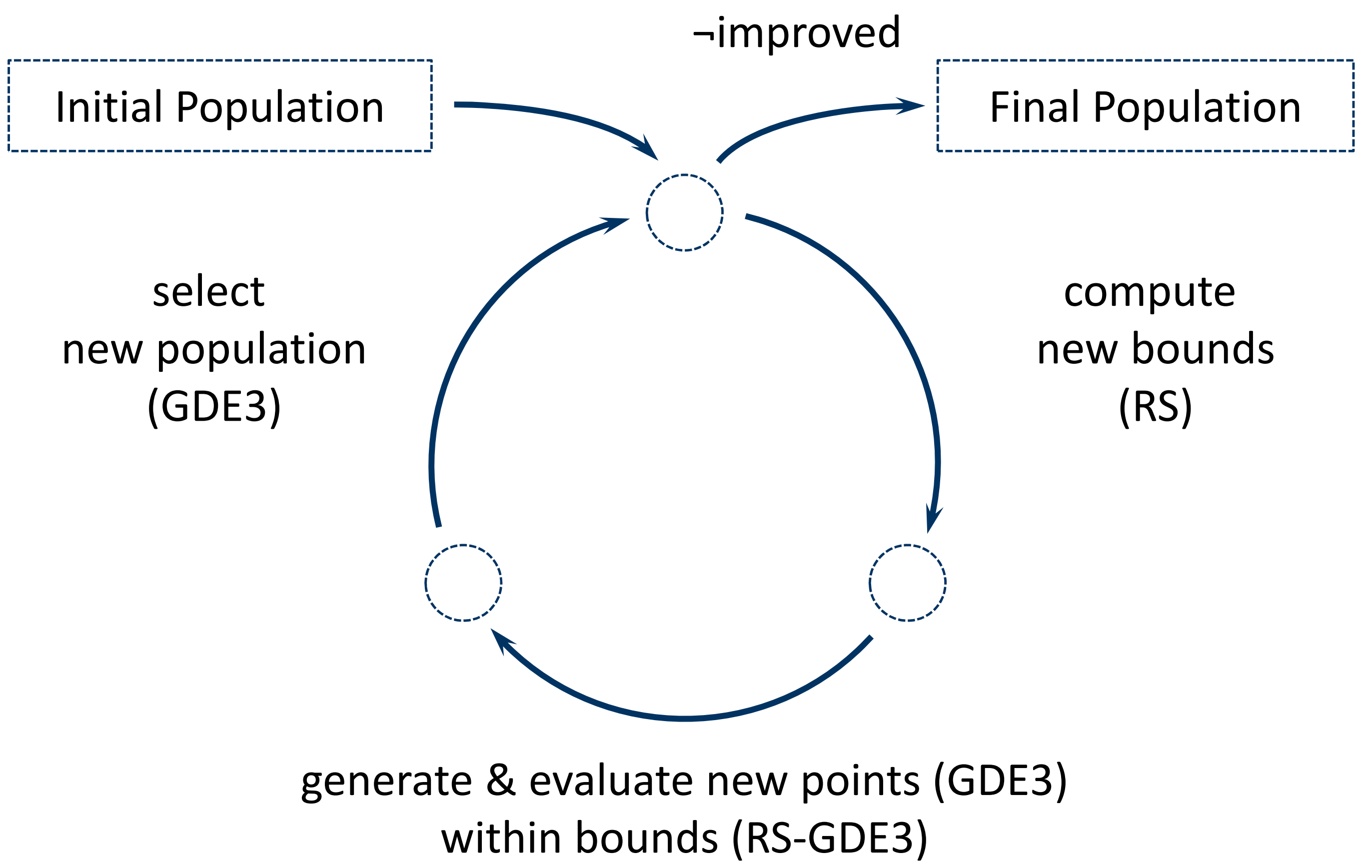
Optimization Algorithm

- Our Algorithm: **RS-GDE3**

- Combination of:
  - Metaheuristics: Evolutionary Computation:
    Differential Evolution algorithm *GDE3*
    - ***Generalized Differential Evolution***
    - => conducts the actual **iterative search**

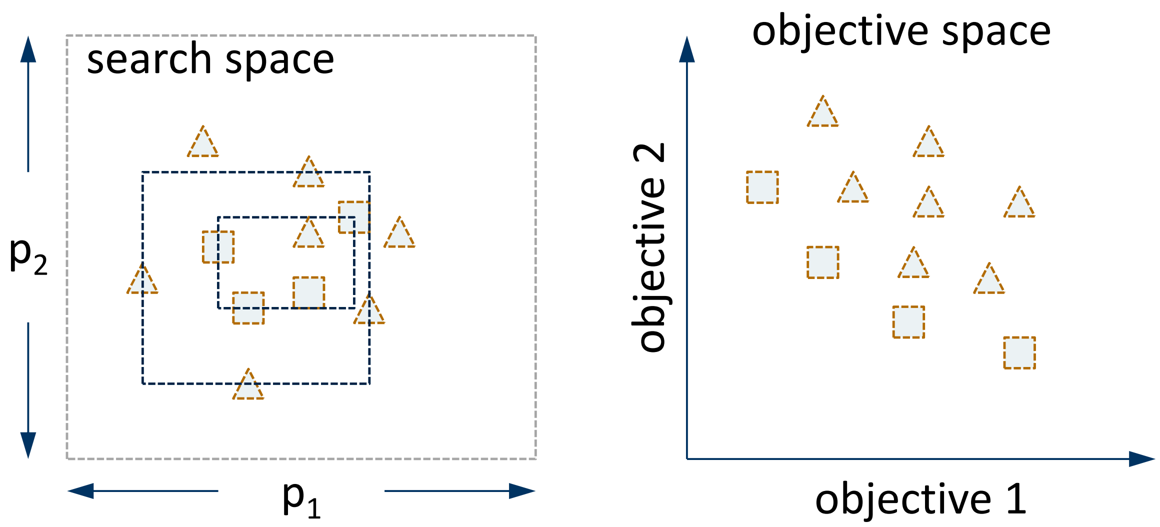
  - ***Rough Set*** based **Search Space Reduction**
    - => domain independent

Optimization Algorithm (2)

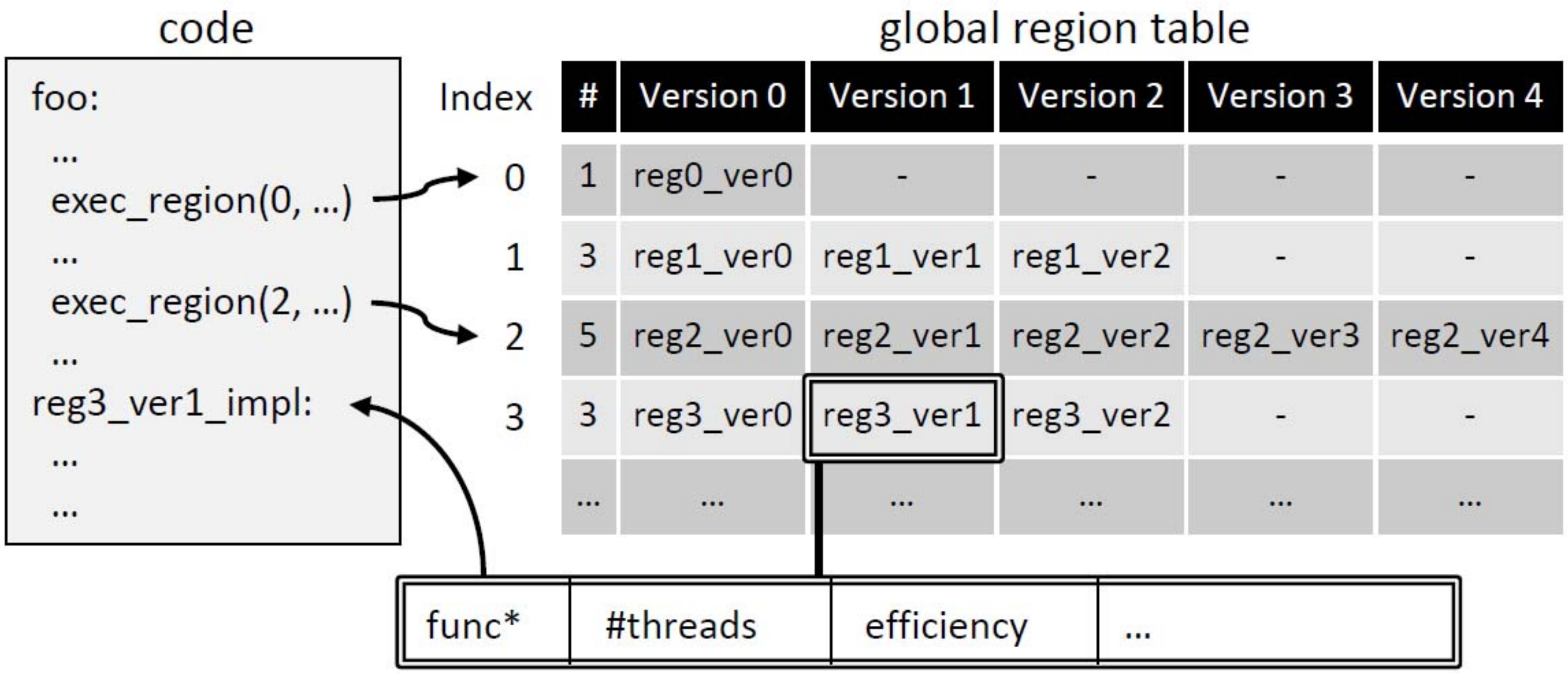


Search Space Reduction (RS)

- Compute bounds by ..
  - Obtaining bounding box of current front
  - Extend to enclosing dominated points



Runtime Version Selection



Experimental Results

Energy as an Optimization Objective

- Optimize 3 objectives simultaneously
  - Energy
  - Runtime
  - Efficiency (costs $c(x) \rightarrow x*t_p(x)$)

- Extra tuning parameter
  - 2/3D Tiling, #threads, **Clock Frequency**
  - Tradeoff between high (fast) energy-demanding frequencies and low (slow) frequencies
  - Larger search space than in the previous experiment

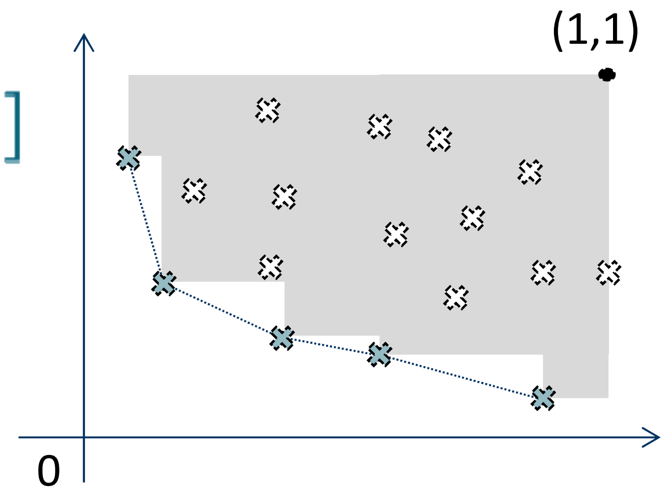
- Clock frequency modified through DVFS
  - Dynamic Voltage and Frequency Scaling

Experimental Setup

- Target architecture:
  - 4 x Intel Xeon SandyBridge with 8cores each / 8x20MB L3 Cache
  - 128 GB of RAM
  - Available clock frequencies from 1.2GHz to 2.6GHz
- Tuning Algorithms:
  - Hierarchical search– search along regular grid
  - RS-GDE3 (our algorithm)
  - Random Search
- Code
  - Matrix multiplication
  - N-body simulation

Comparing Algorithms

- Quality of Solution $\boldsymbol{S}$:
  - Hypervolume: $\boldsymbol{V}(\boldsymbol{S}) \in [0 \dots 1]$
  - Number of Points: $|\boldsymbol{S}|$

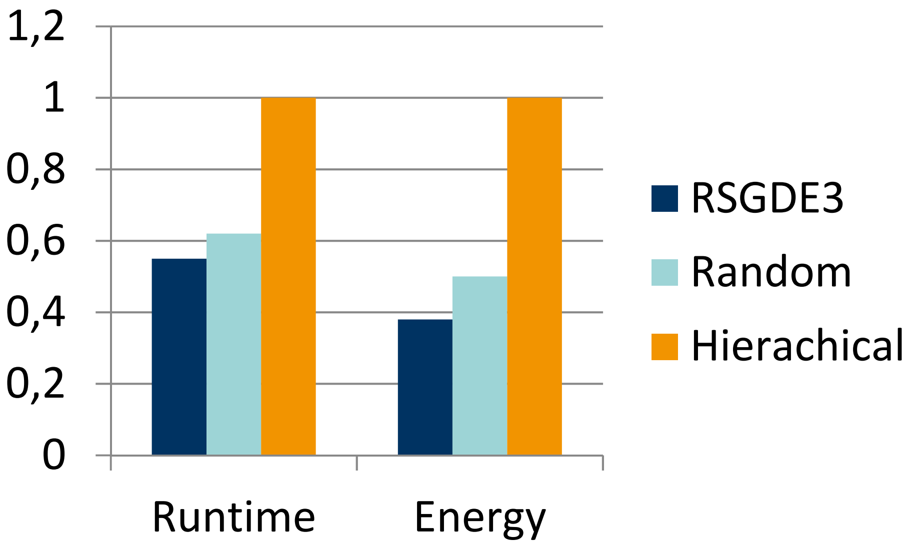


- Efficiency of Algorithm:
  - Number of evaluated Configurations $\boldsymbol{E}$

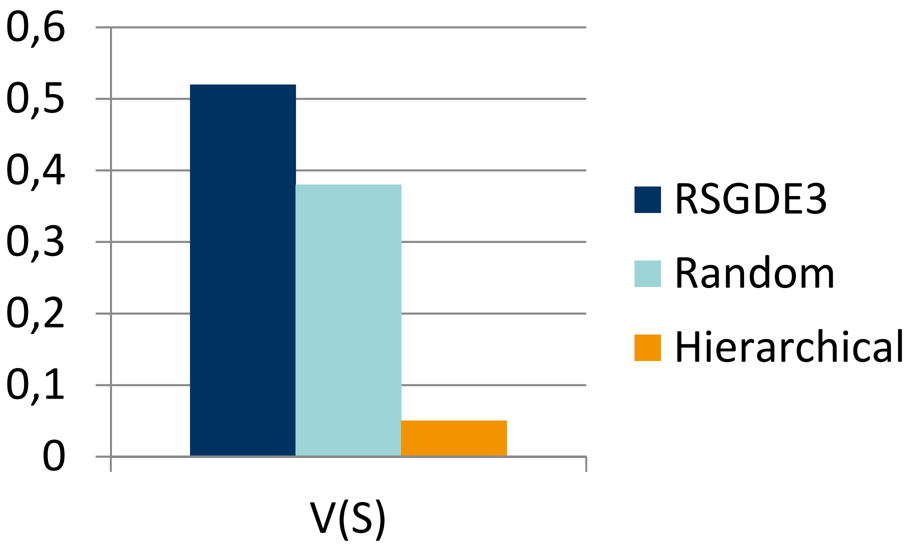
- For stochastic Algorithms: $\overline{\boldsymbol{V}(\boldsymbol{S})}$, $\overline{|\boldsymbol{S}|}$ and $\overline{\boldsymbol{E}}$

Obtained Results

- RSGDE3 only requires to evaluate less than 0.000013% of all possible configurations
- Comparing the fastest solutions
  - > 70% more energy efficient than hierarchical
    - 45 % faster
  - 24 % less energy consumption than random search
    - 14 % faster
- The hypervolume also shows the higher quality of the Pareto fronts computed by RSGDE3

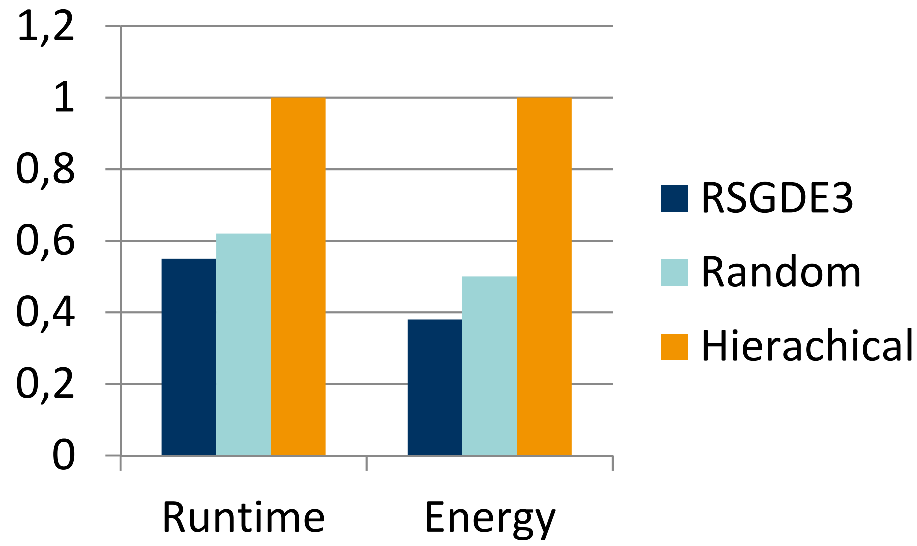


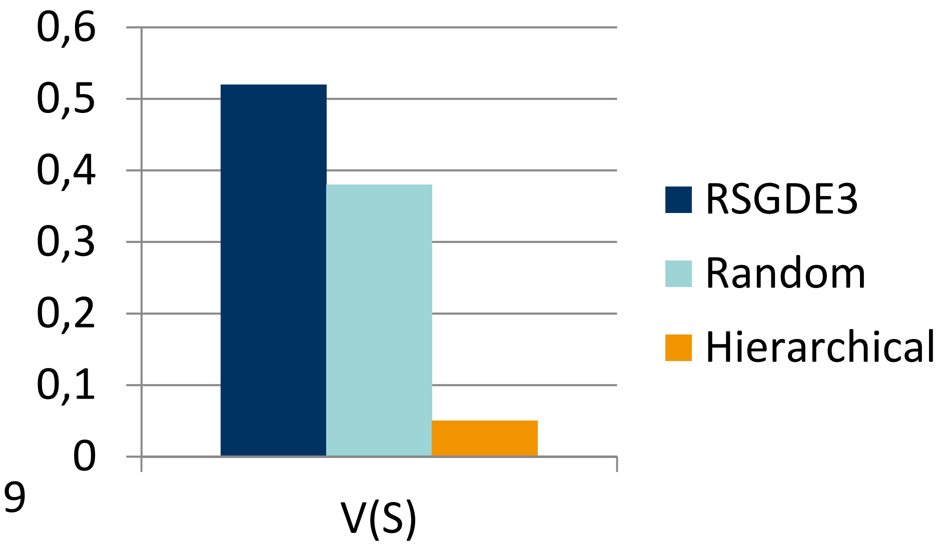
Data normalized to the (0 ,1) interval



Obtained Results (2)

- RSGDE3 only requires 6% of the evaluations performed by Random and hierarchical
- Random reports better results than hierarchical
  - Showing the non suitability of hierarchical search for exploring extremely large search spaces



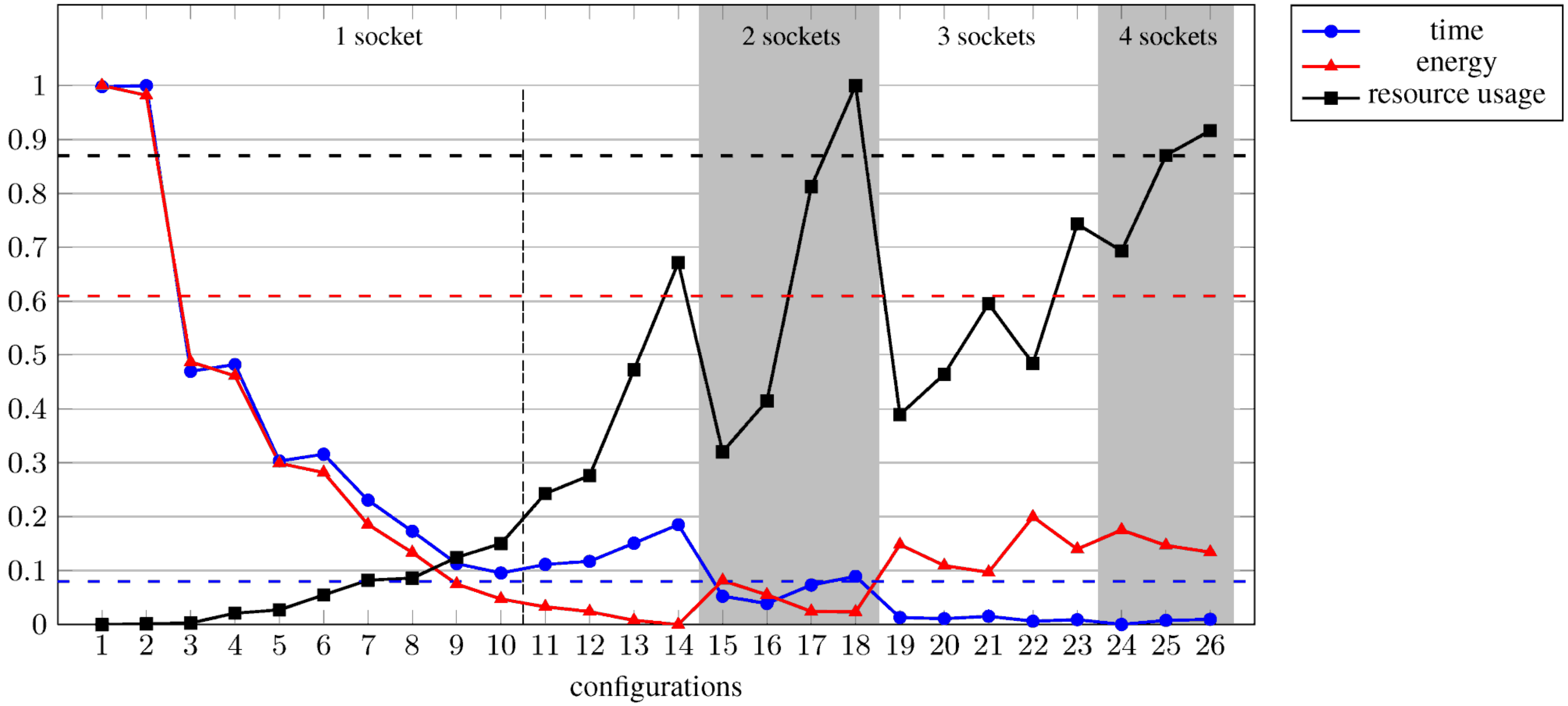


Performance Comparison

Benchmark	Hierarchical Search				Random Search			
	N	|S|	|S|'	V(S)	N	|S|	|S|'	V(S)
mm	18432	18	2%	0.00	15000	4.4	0%	0.33
dsyrk	18432	21	5%	0.00	15000	2.2	11%	0.17
jacobi-2d	15876	31	78%	0.69	15000	17.2	5%	0.55
3d-stencil	15876	30	22%	0.75	15000	24.8	60%	0.61
n-body	15876	26	0%	0.50	15000	30	17%	0.70

Benchmark	RS-GDE3			
	N	|S|	|S|'	V(S)
mm	956.2	23.4	98%	0.48
dsyrk	1149.6	24.8	98%	0.32
jacobi-2d	1243.6	29.8	75%	0.76
3d-stencil	981.4	28.2	77%	0.76
n-body	1801.4	29.6	87%	0.77

Trade-offs among 3 Objectives for n-body



Region-Aware Auto-Tuning

- Most existing auto-tuners
  - global tuning finds fixed parameter values for the entire program.
  - assumes that fixed parameter values achieve best performance across all regions.
- Programs may consist of many code regions
  - code region specific parameter values may yield best performance
  - changing parameter values implies overhead
- Region based Auto-tuning increases search space

Motivating Example

```
#pragma omp parallel for
for (int i=0; i<N; i++) {
   for (int j=0; j<K; j++) {
       for (int k=0; k<M; k++) {
          C[i][j] += A[i][k] * B[k][j];
       }
   }
}
```

scales well

```
for (int i=0; i<N/4; i++) {
   for (int k=0; k<M/4; k++) {
      #pragma omp parallel for
      for (int j=0; j<K/4; j++) {
         C[i][j] += A[i][k] * B[k][j];
      }
   }
}
```

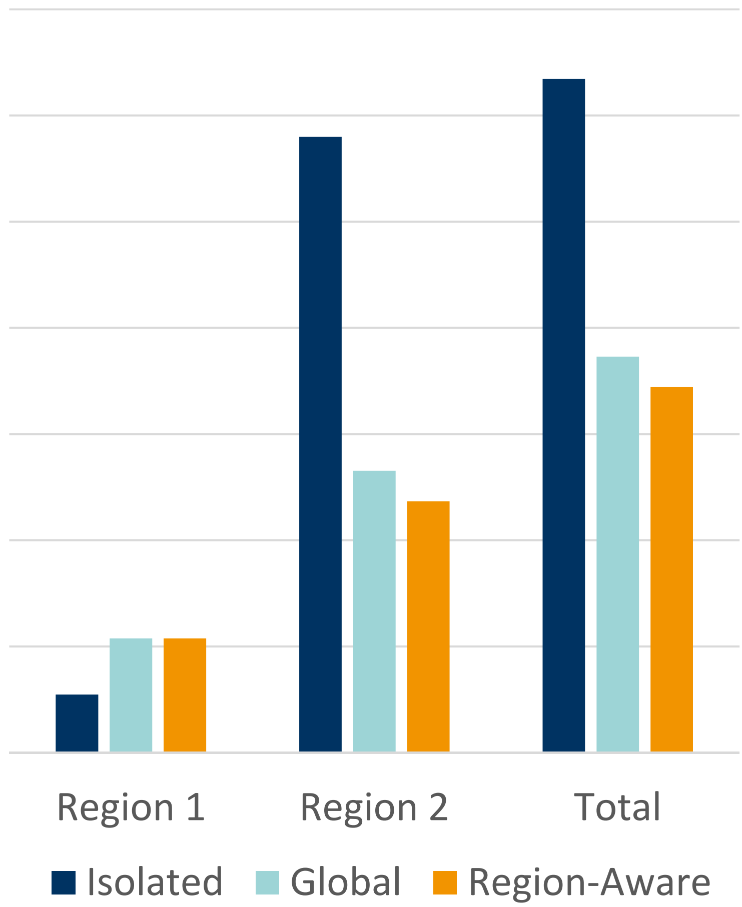
doesn,t scale well

Region-Aware Auto-Tuning Approaches

- Isolated
  - Tune regions individually following the control flow
  - Ignores overhead for changing parameter values
- Global
  - Same parameter values for the entire program
- Region-Aware
  - tunes all regions simultaneously
  - Individual parameter values for each region
  - Optimizes the overal program performance
  - Considers overhead for changing parameter values

Motivating Example

	Isolated	Global	Region-Aware
#Threads Region 1	20	10	10
#Threads Region 2	2	10	7
Region 1	546	1075	1075
Region 2	5798	2652	2366
Total	6344	3727	3442



Challenges of Region-Aware Auto-Tuning

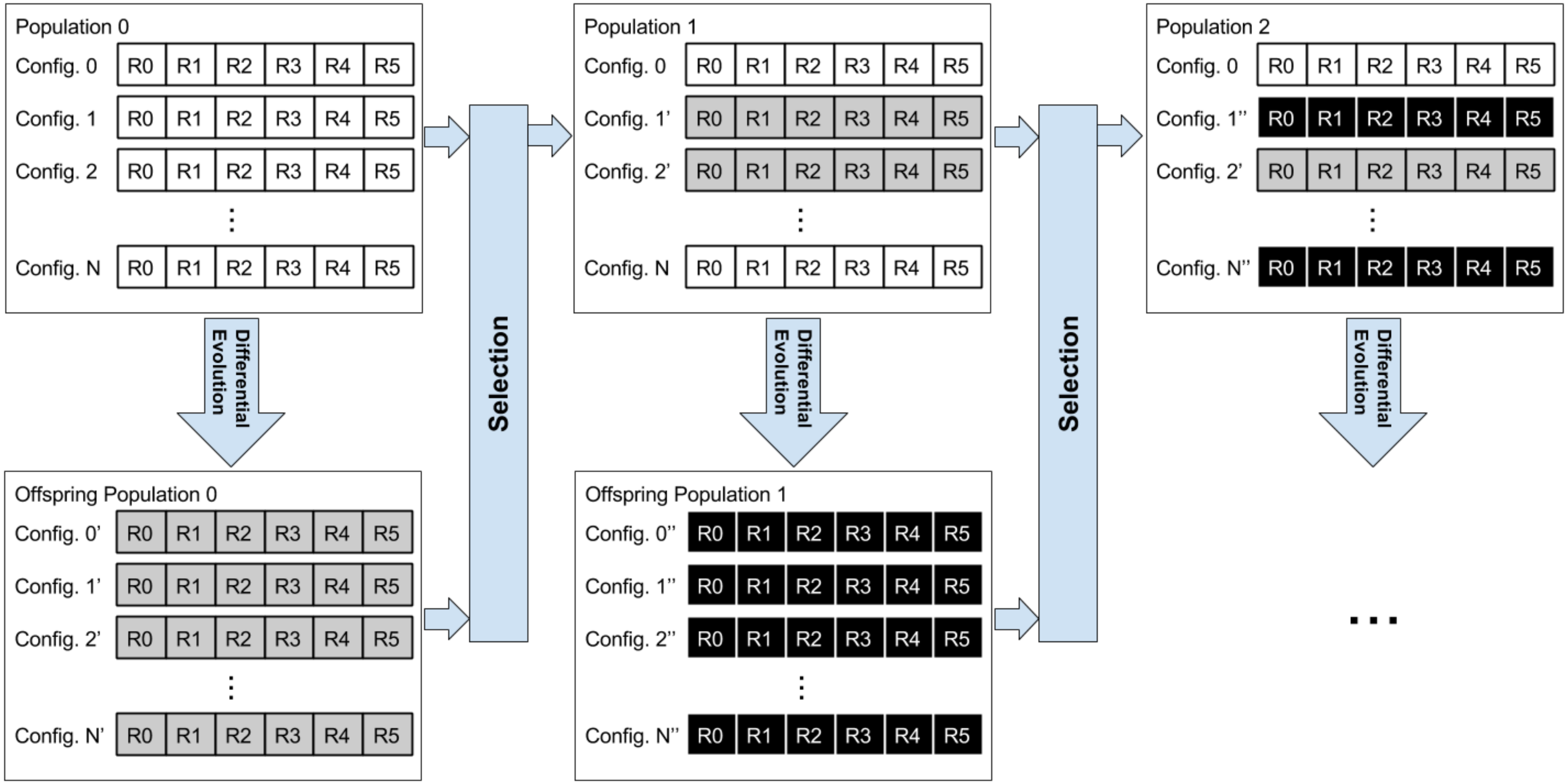
- Region dependencies
  - Settings of one region may affect performance of others
- Consistent goal
  - Settings of all regions should optimize for the same trade-off solution
- Huge search space
  - Growing exponentially with number of regions

Extentions to the Region-Aware RS-GDE3*

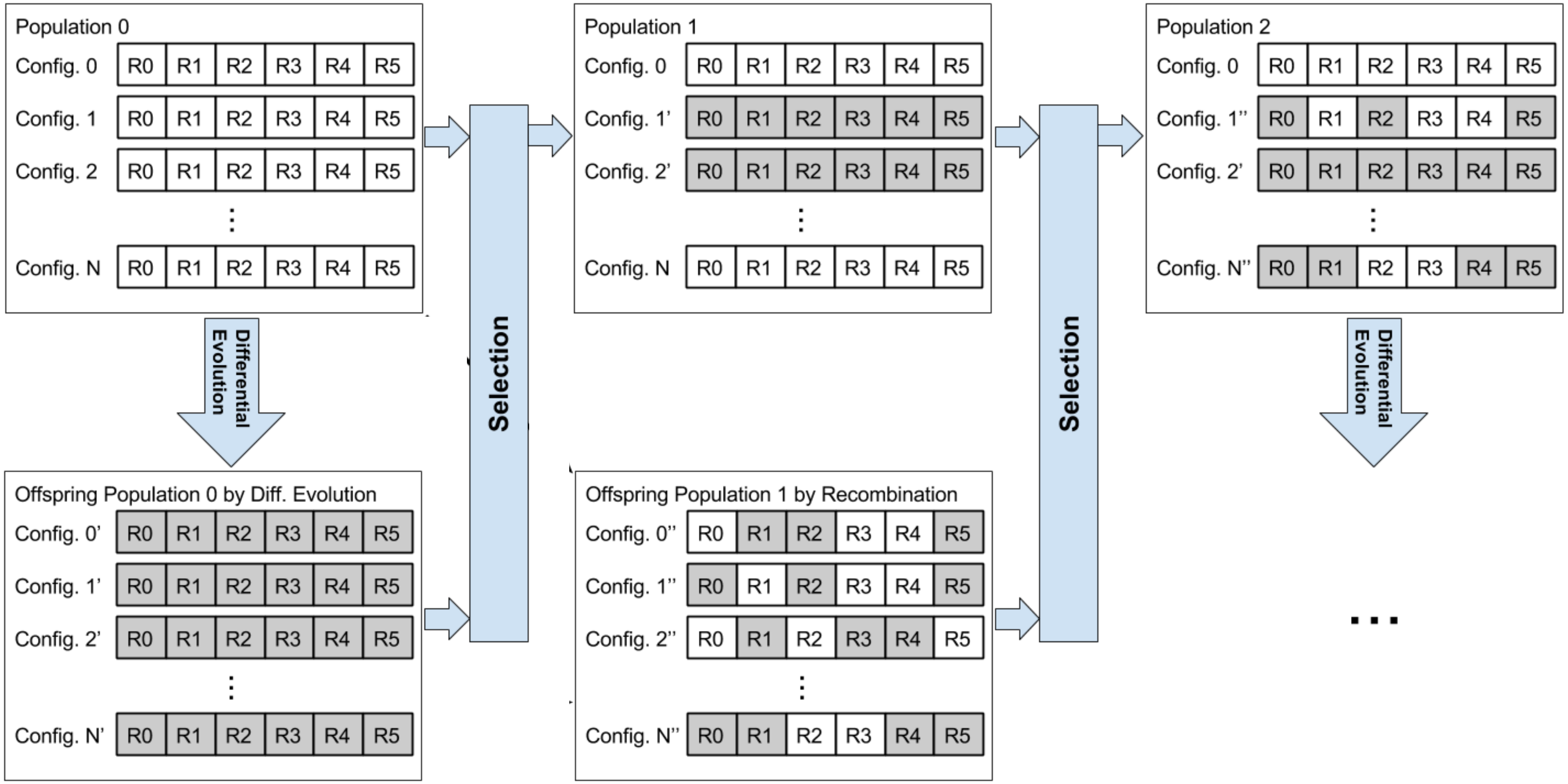
- Global pre-tuning phase
  - Using global tuner for first iterations
  - Reduces initial search space
  - Quickly converge to a reasonable starting point
  - Avoid overheads between regions
- Recombination
  - Avoid purging of good local solutions
  - Combine parameter values optimizing same objective
  - Maximizing the likelyhood of reusing good parameter values per regions

* K. Kofler, J. Durillo, P. Gschwandtner, T. Fahringer. A region-aware multi-objective auto-tuner for parallel programs. P2S“, Bristol, UK, Aug. 2017.

Region aware GDE3



Region aware GDE3 with Recombination



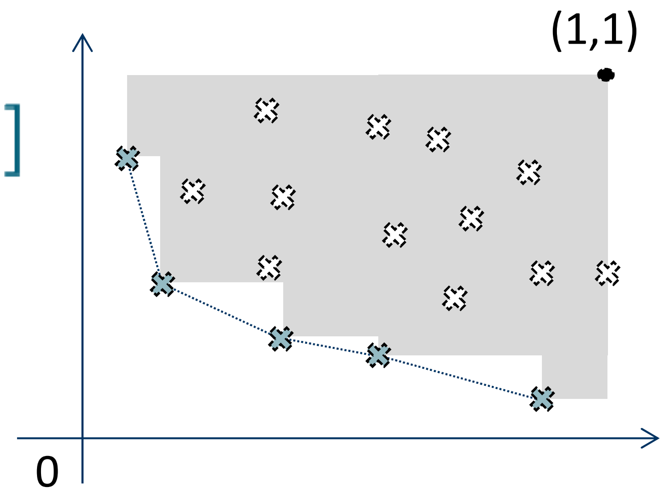
Experimental Results

Architectures

- Two multi-socket Intel Xeon
  - Intel Xeon E5-2690 v2 (Ivy Bridge-EP), 20 cores
  - Intel Xeon E5-4650 CPU (Sandy Bridge-EP), 32 cores
- Three benchmarks
  - bt (block tri-diagonal solver from NAS parallel benchmarks)
  - mg (three-dimensional discrete Poisson equation from NAS parallel benchmarks)
  - Heated-plate (stencil-code solving the steady heat equation)

Comparing Tuners

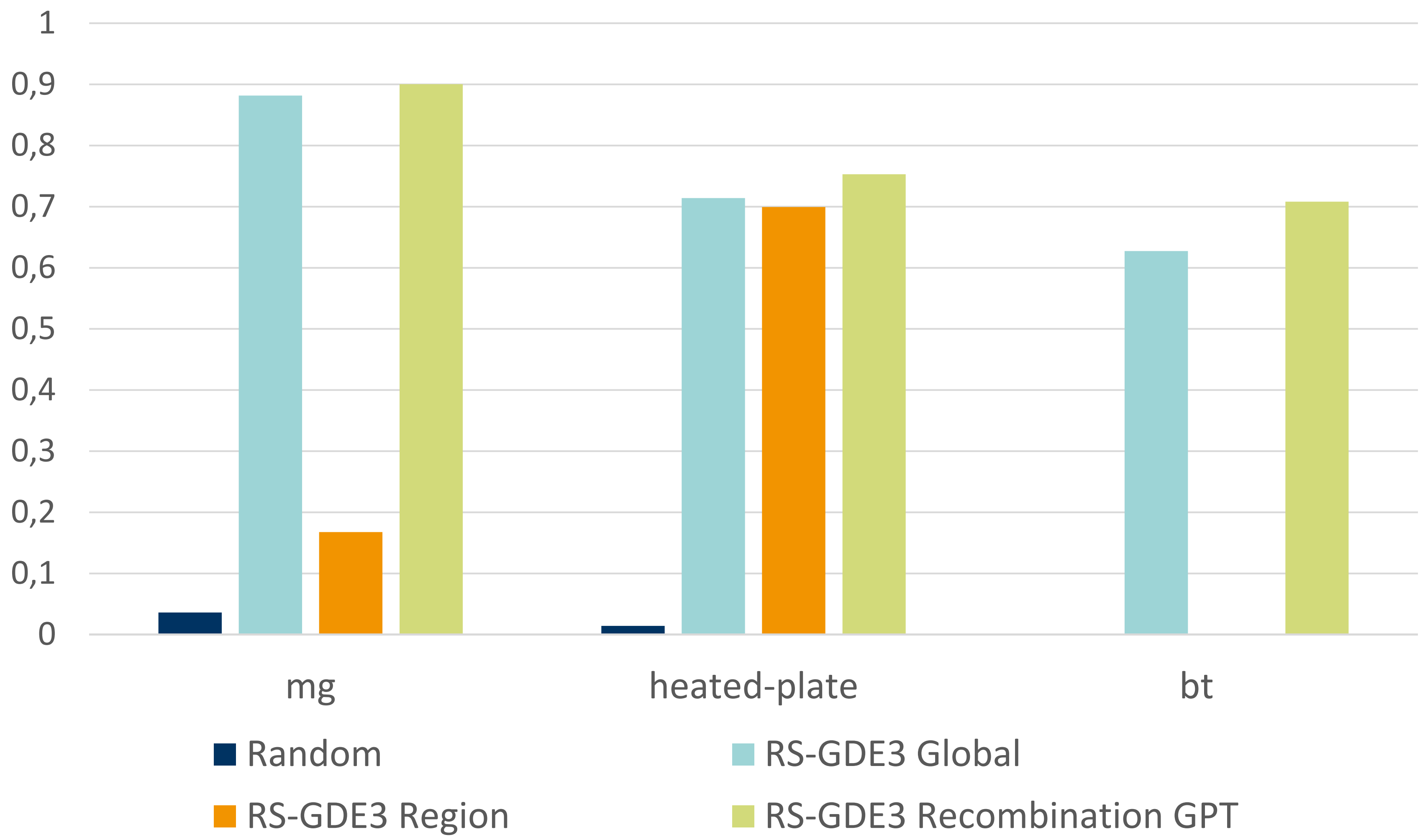
- Quality of Solution $\boldsymbol{S}$:
  - Hypervolume: $\boldsymbol{V}(\boldsymbol{S}) \in [0 \dots 1]$
  - Number of Points: $|\boldsymbol{S}|$



- Efficiency of Algorithm:
  - Number of evaluated Configurations $\boldsymbol{E}$

- For stochastic Algorithms: $\overline{\boldsymbol{V}(\boldsymbol{S})}$, $\overline{|\boldsymbol{S}|}$ and $\overline{\boldsymbol{E}}$

Hypervolume

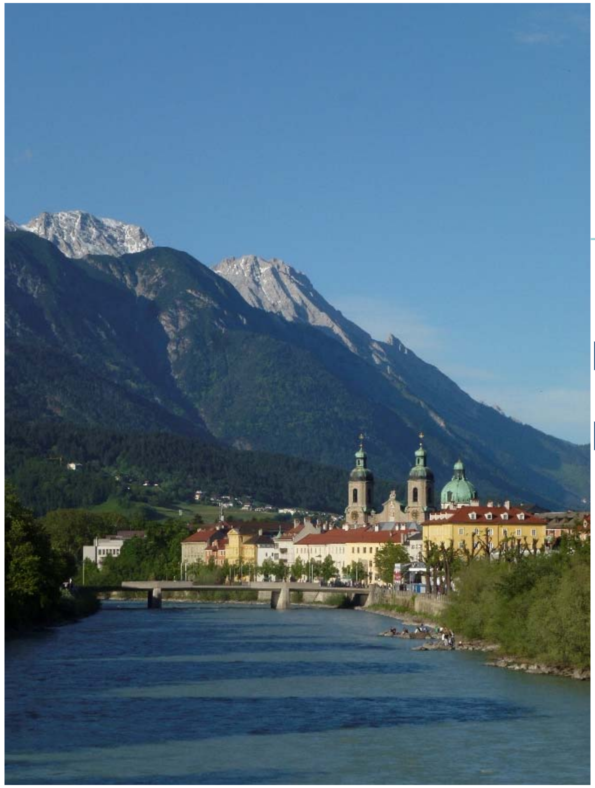


Tuning Time

	mg	heated-plate	bt
Random	26913.5	30706	31431.5
RS-GDE3 Global	17871	12365	21246
RS-GDE3 Region	25088	16712.5	30997.5
RS-GDE3 Recombination GPT	21209	13237	25162.5

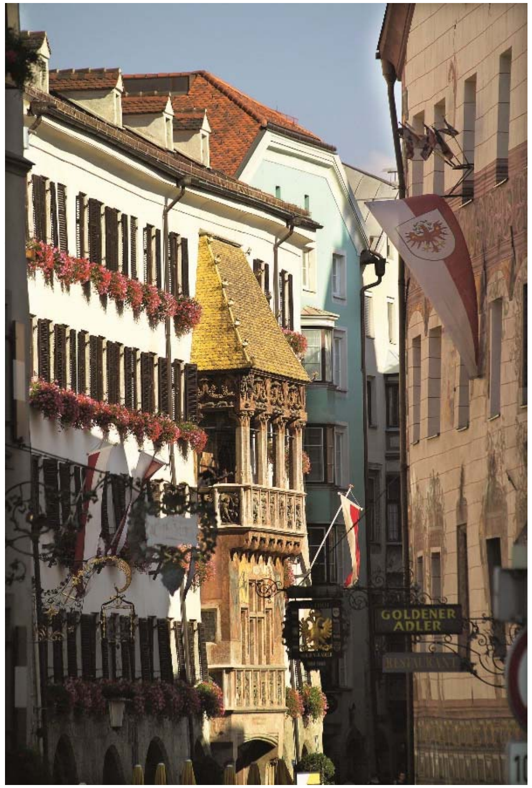
Conclusion

- motivated the **usefulness for multi-objective** optimization and auto-tuning within compilers
- developed a suitable **generic optimizer algorithm** RS-GDE3 for an arbitrary number of objectives
- demonstrated its **effectiveness** on tuning tiled parallel loops for 3 objectives:
  - runtime
  - resource utilization
  - Energy
- Region aware auto-tuner
  - Up to 7x faster than un-optimized code
  - Up to 17% improvement over traditional auto-tuner



Thank you!

- Further Information:
- http://www.insieme-compiler.org/



- Insieme Funding as part of European projects:
  - H2020 FETHPC AllScale
  - Chist-era Gemsclaim
  - Interreg IV En-act
  - NoE Hipeac
  - ICT Cost Action NESUS