Vertically-integrated exploration of algorithmic and implementation design spaces in 3D scene understanding

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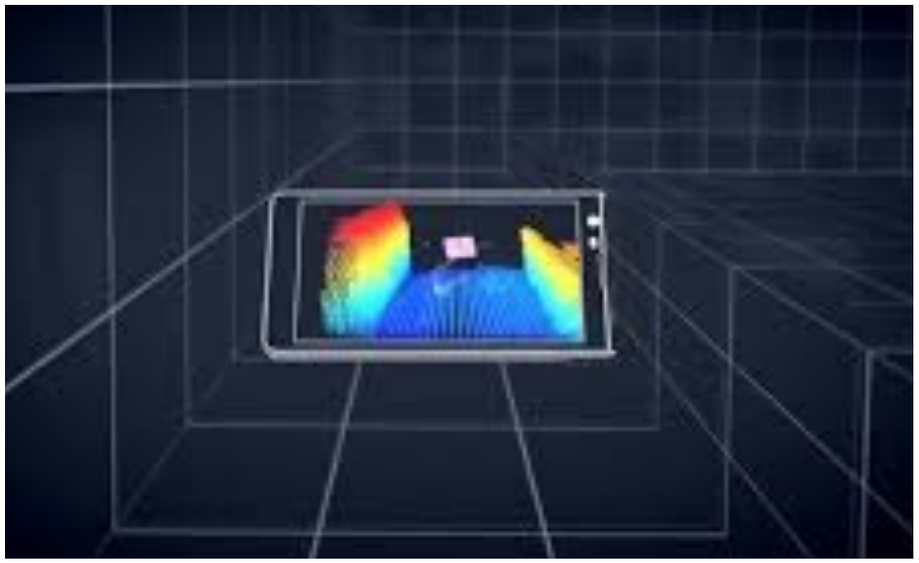
Luigi Nardi - Imperial College London

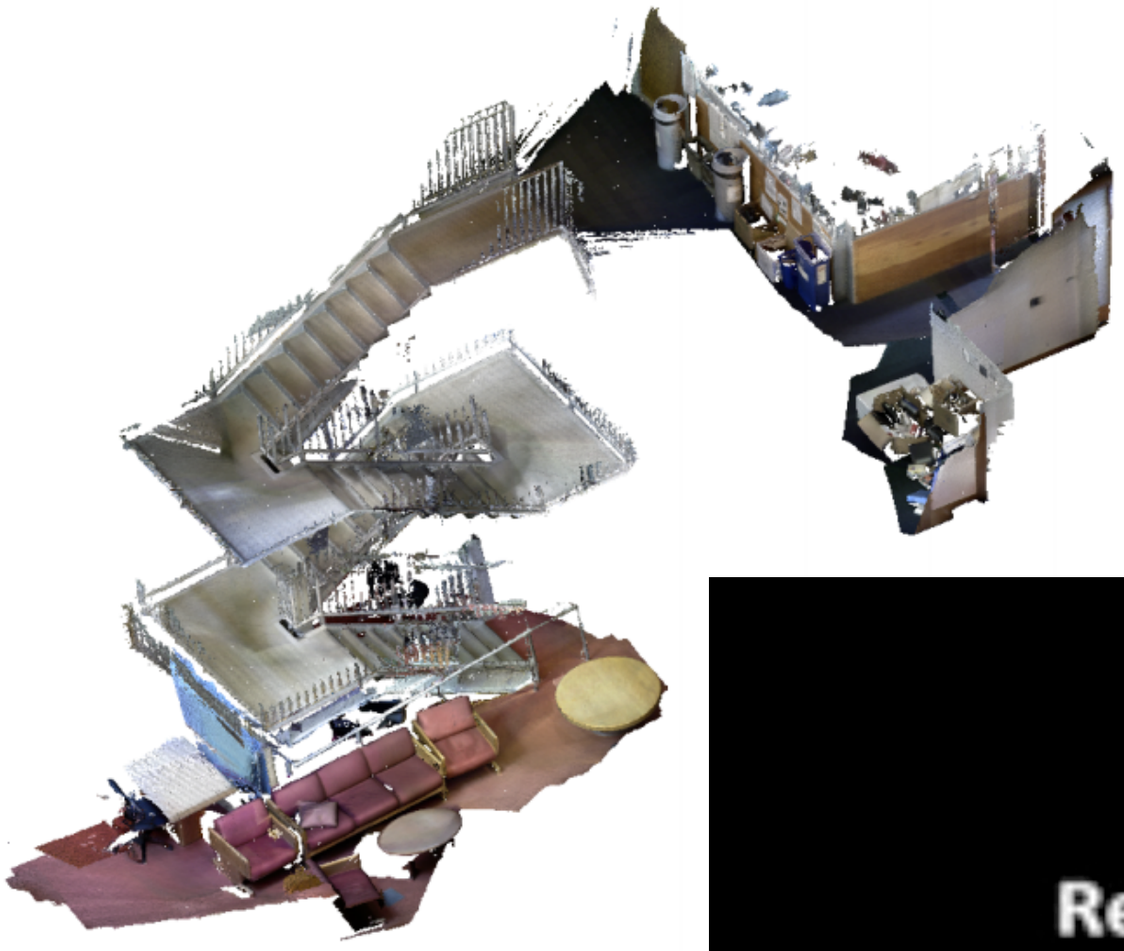
Simultaneous localisation and mapping (SLAM)

Build a coherent world representation and localise the camera in real-time

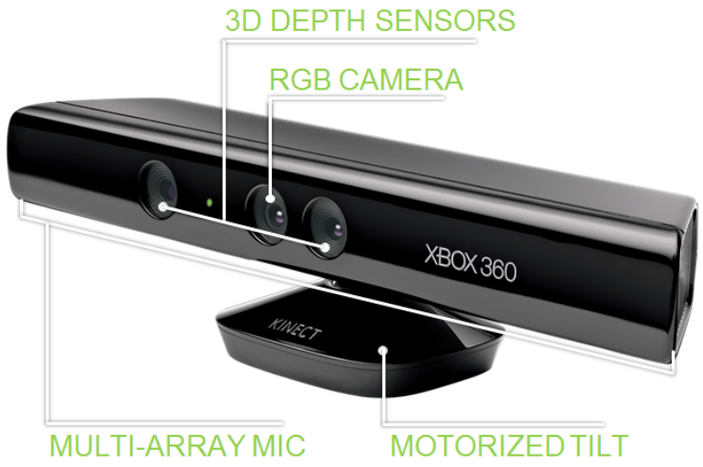


Video:
Dyson 360 Eye

Simultaneous localisation and mapping (SLAM)



[Whelan et al. 2012]



Video:
[Newcombe et al. ISMAR 2011]

Three “Performance” metrics

Holistic approach to SLAM “performance”:

SLAMBench

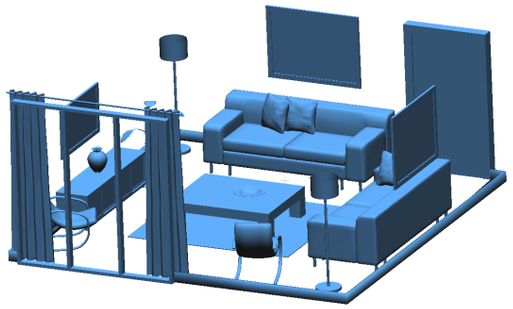
Computer Vision

Compiler/Runtime

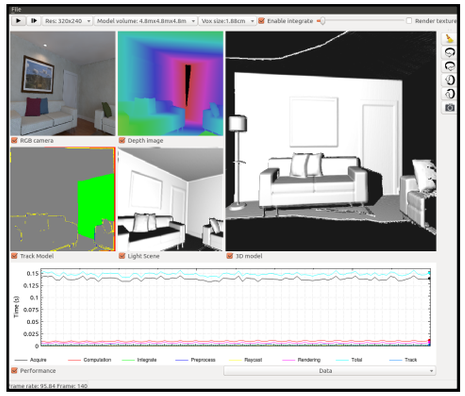
Kernels → **Architectures** → **Correctness** → **Performance** → **Metrics**

```
bilateralFilter (..)
halfSampleRobust (..)
renderVolume (..)
integrate (..)
      :
      :
```

Hardware



ICL-NUIM Dataset

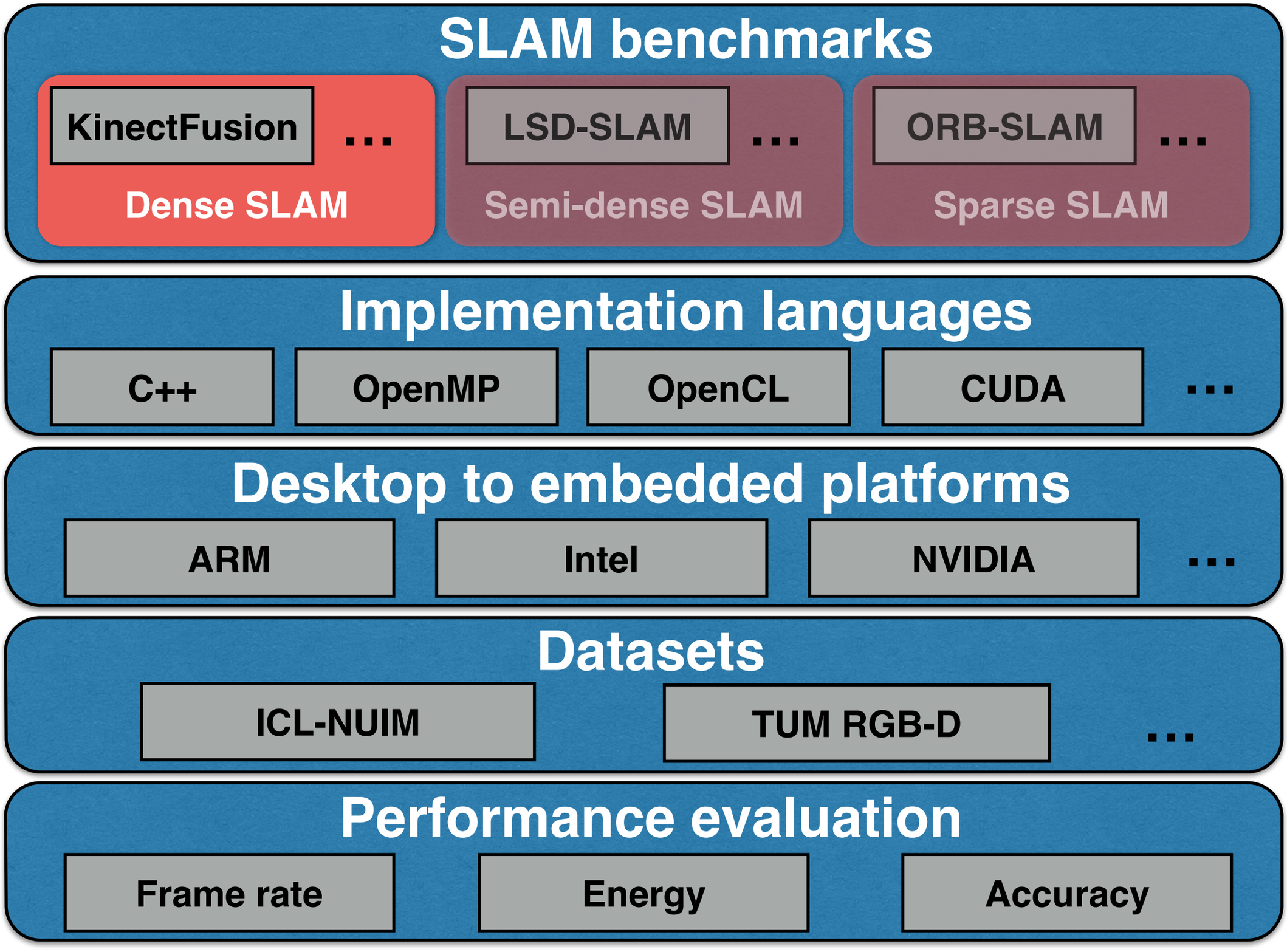


Frame rate

Energy

Accuracy

SLAMBench framework



[Nardi et al., 2015]

“Performance” on SLAMBench

- Runtime/energy/accuracy measurements
- Accuracy provided via absolute trajectory error (ATE)

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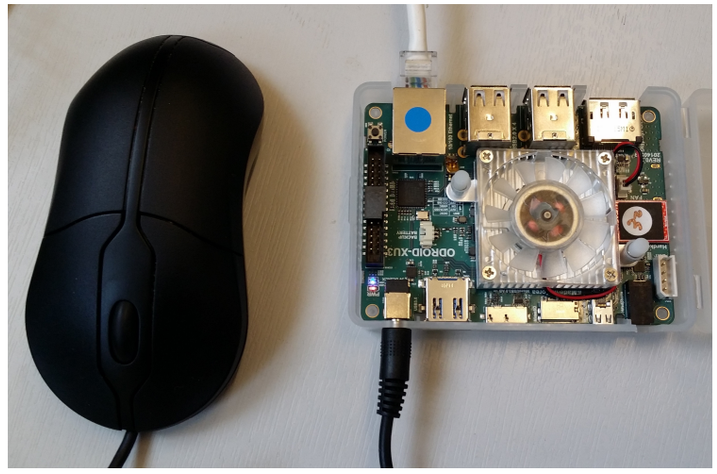
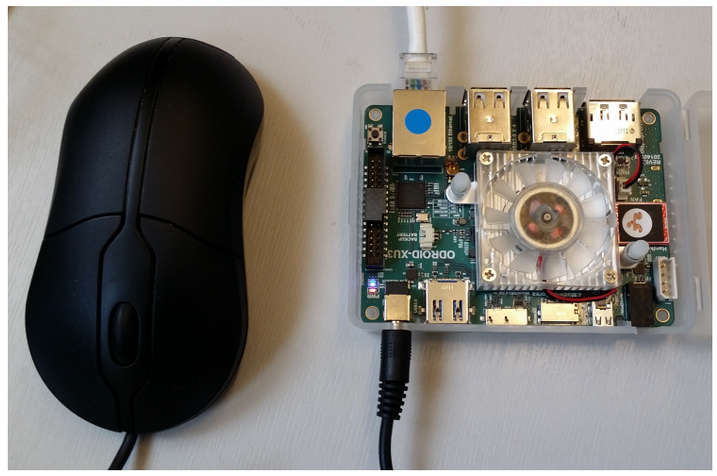


Machine	CPU	CPU name	CPU GFLOPS	CPU cores	GPU	GPU name	GPU GFLOPS	TDP Watts
Hardkernel ODROID-XU3	ARM A15 + A7	Exynos 5422	80	4 + 4	ARM	Mali-T628	60 + 30	10

“Performance” on SLAMBench



- Runtime/energy/accuracy measurements
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ATE in cm	
C++	2.06
OpenMP	2.06
OpenCL	2.01

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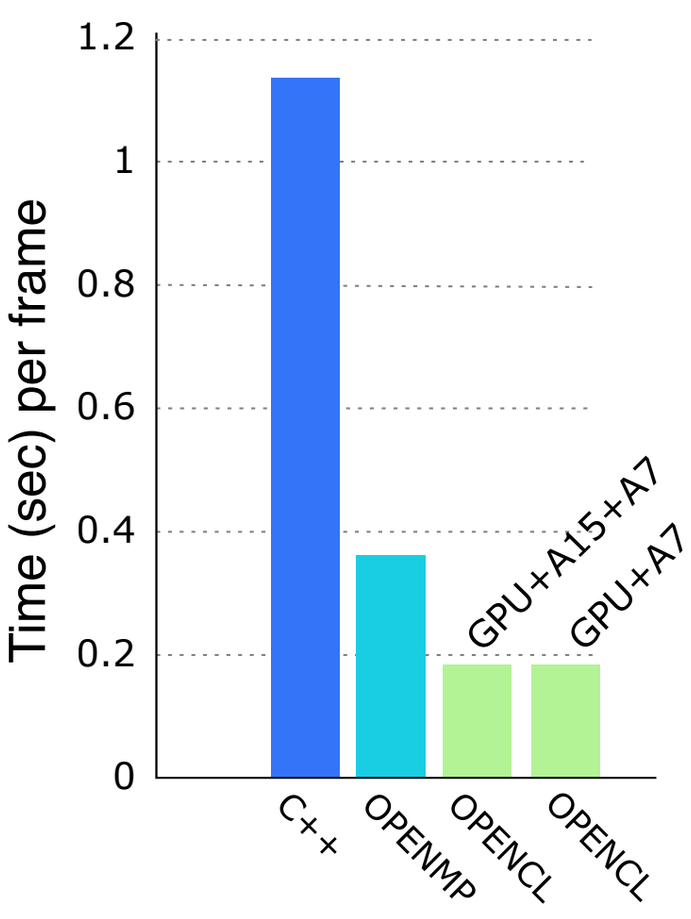
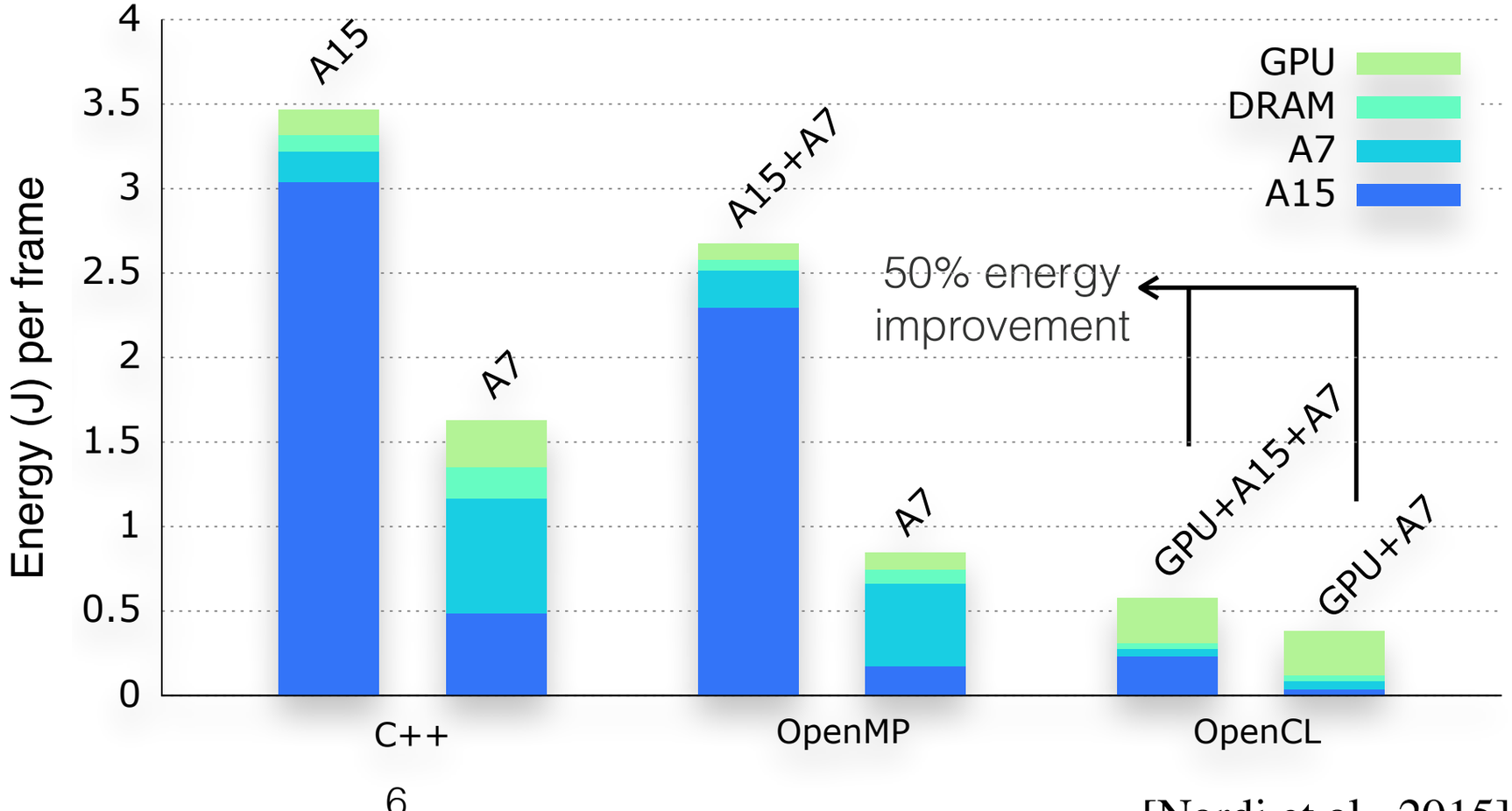




[Nardi et al., 2015]

SLAMBench today

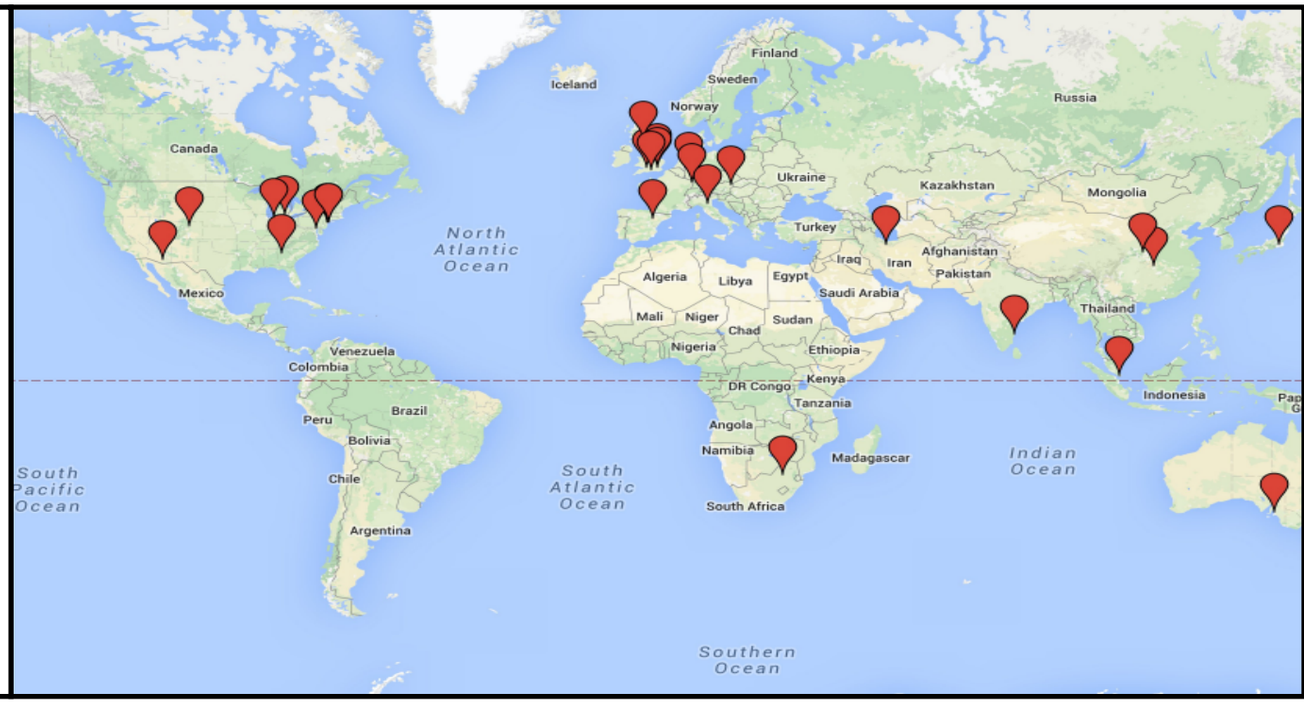
- Publicly released 13/11/2014 (800+ downloads)

- Early adopters:
  - Computer Vision
  - Compiler/runtime
  - Architecture

Company users

AMD, ocado, dyson, ARM, Texas Instruments, Microsoft, amazon, NVIDIA, QUALCOMM, Imagination, IBM, Google, codeplay, Movidius, SAMSUNG, intel, TOYOTA, atheer labs, magic leap

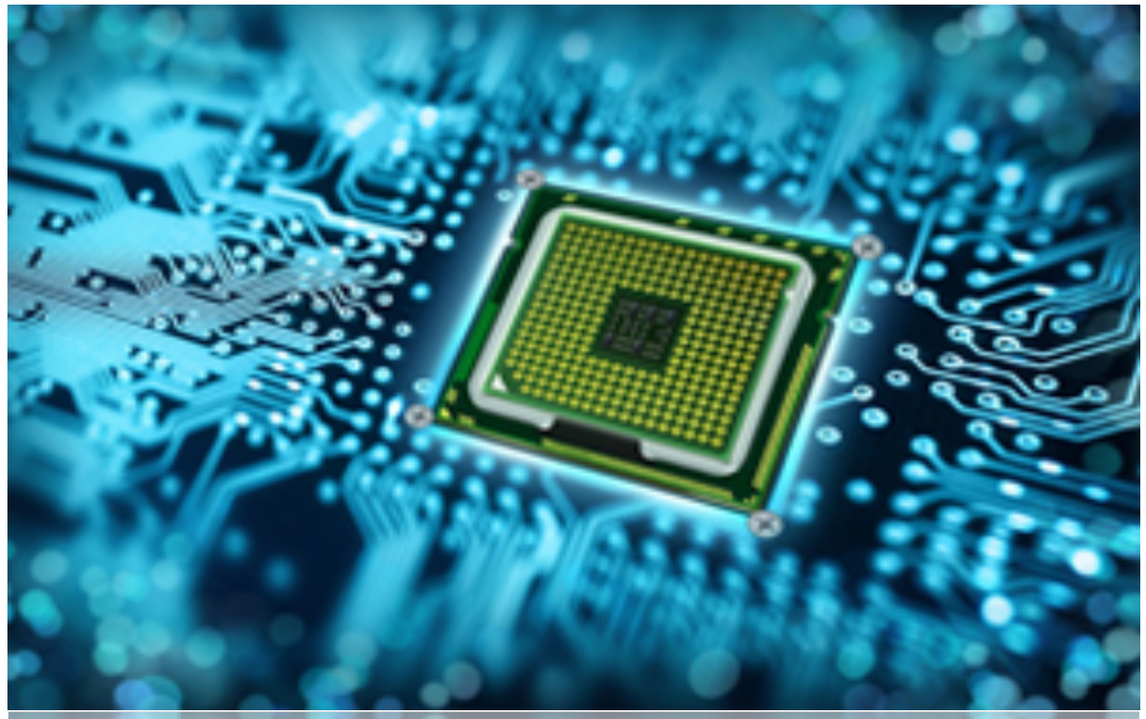
Academic users



Web: apt.cs.manchester.ac.uk/projects/PAMELA/tools/SLAMBench/

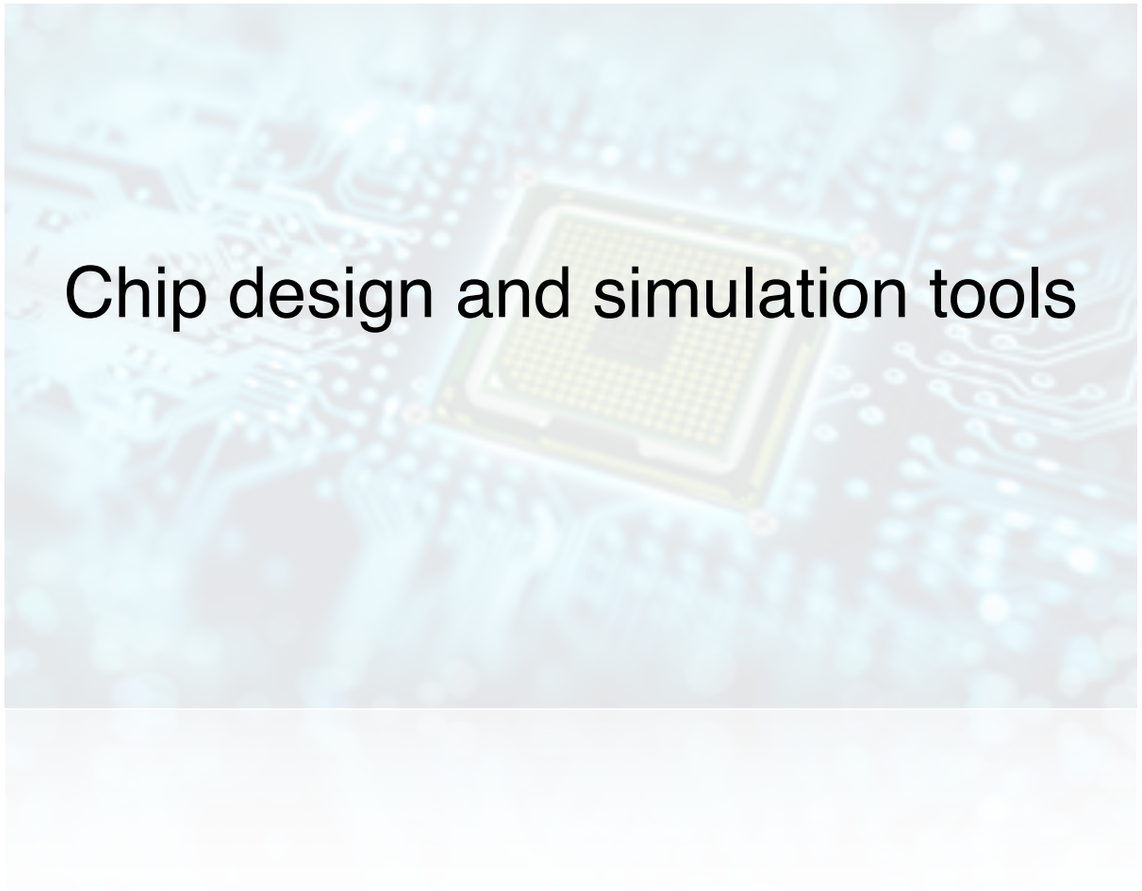
Paper: ***Introducing SLAMBench, a performance and accuracy benchmarking methodology for SLAM"*, arxiv.org/abs/1410.2167**

SLAMBench opportunities



Chip design and simulation tools

SLAMBench opportunities



SLAMBench opportunities

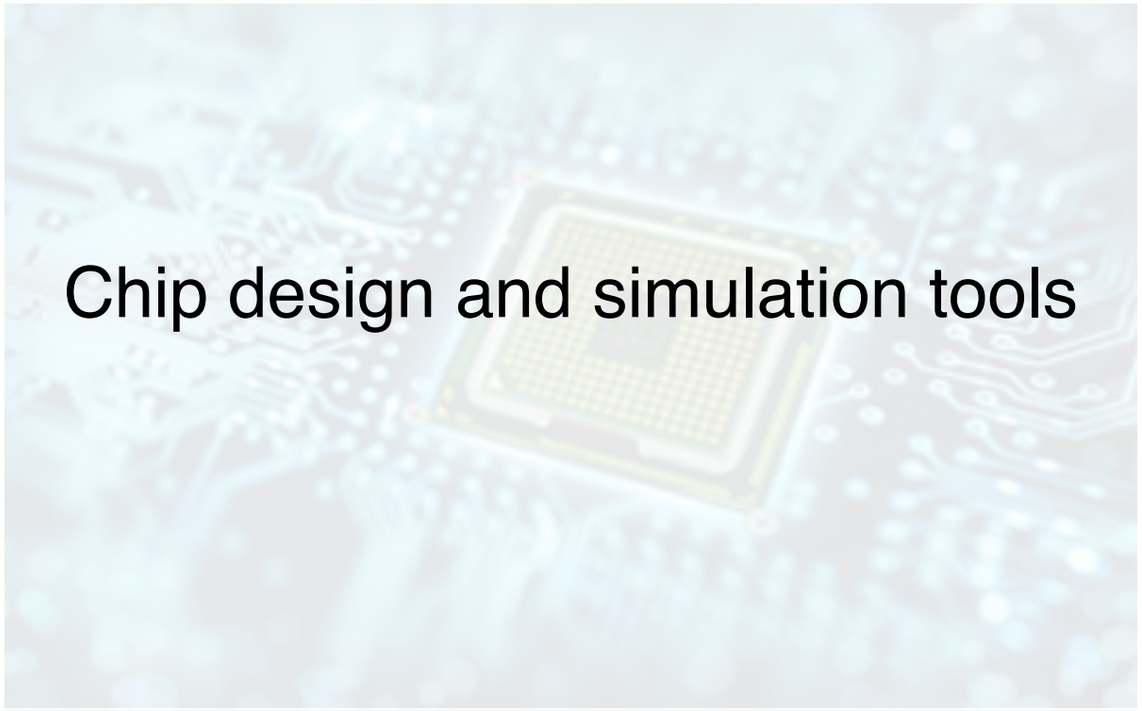
Chip design and simulation tools

SLAMBench evolution:

- Point fusion
- Octrees
- Semi-dense SLAM
- Feature-based SLAM

Kernels can be improved individually

SLAMBench opportunities



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Domain-specific language (DSL) targeting high performance, low-power solutions

Design-space exploration, e.g. algorithmic, compiler and hardware parameters

SLAMBench kernels tuning, e.g. vectorisation, GPU, auto-tuning

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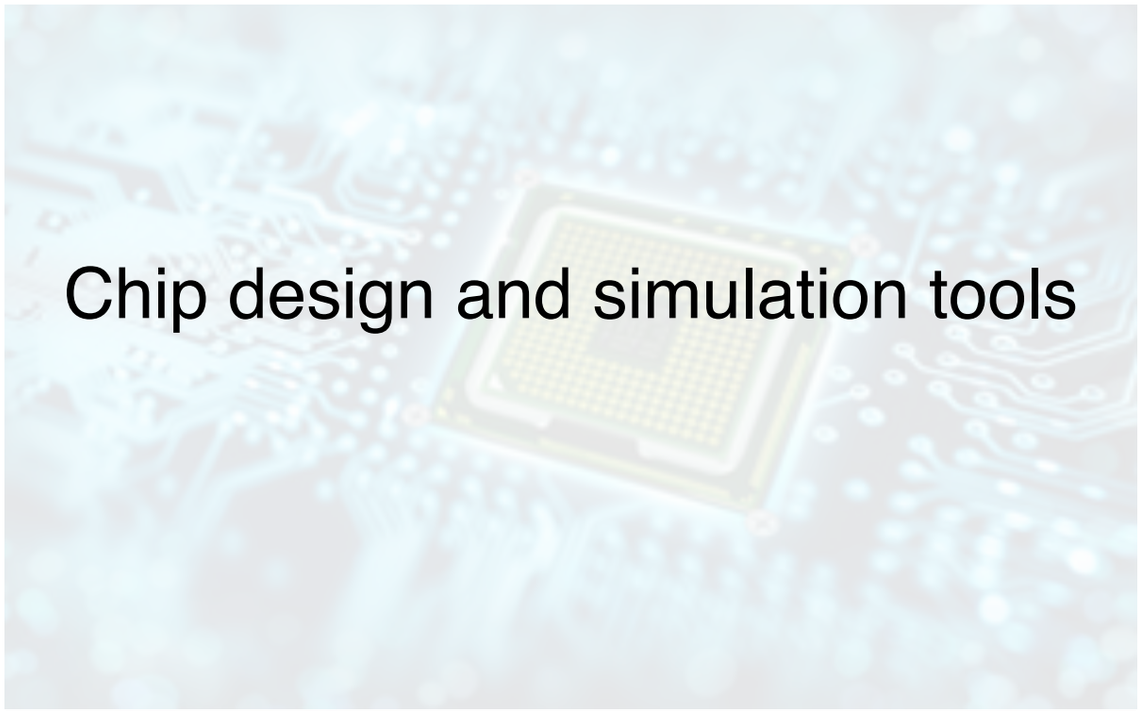

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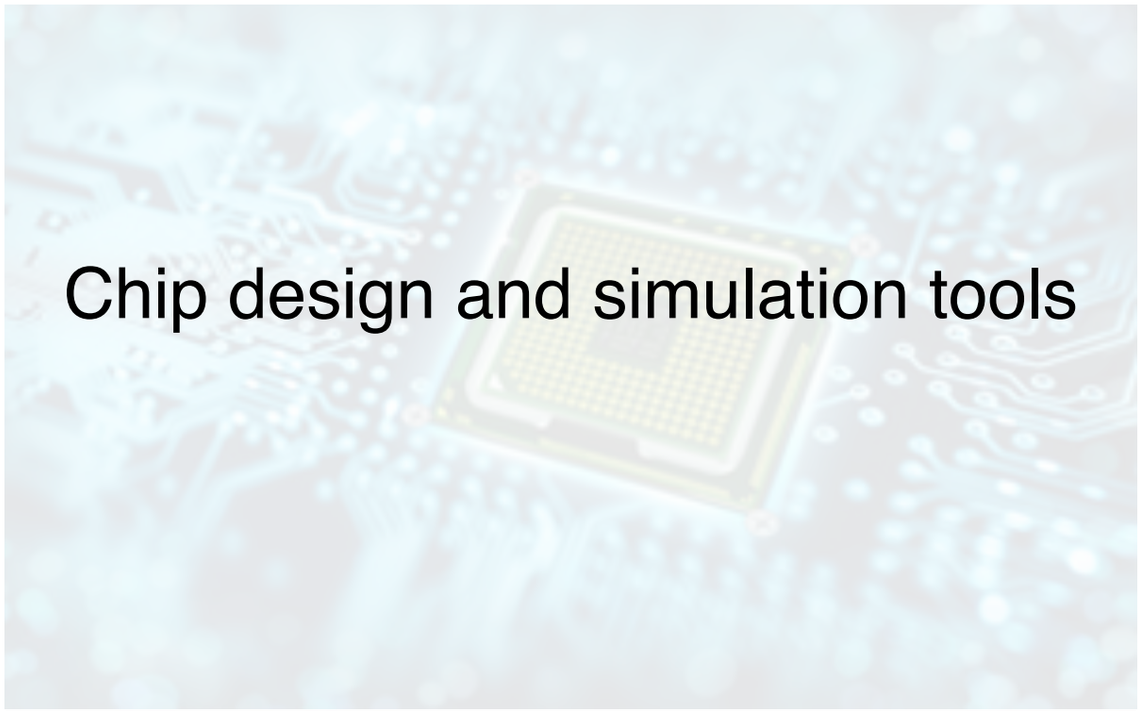

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Kernels can be improved individually

- CPU/GPU mapping/partitioning
- Just-in-time compilation

What is the optimisation space?

Configuration parameters:

Space 1

1. Algorithmic:
   - Application-specific parameters
   - Minimisation methods
   - Early exit condition values

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   - LLVM flags: O1, O2, O3, vectorize-slp-aggressive, etc.
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Space 3

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Warning: huge spaces, impossible to run exhaustively

KinectFusion algorithmic features

Features	Ranges
Volume resolution	64x64x64, 128x128x128, 256x256x256, 512x512x512
μ distance	0 .. 0.5
Pyramid level iterations (3 levels)	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
Image resolution (image ratio)	1, 2, 4, 8
Tracking rate	1, 2, 3, 4, 5
ICP threshold	10^{-6} .. 10^{2}
Integration rate	1 .. 30

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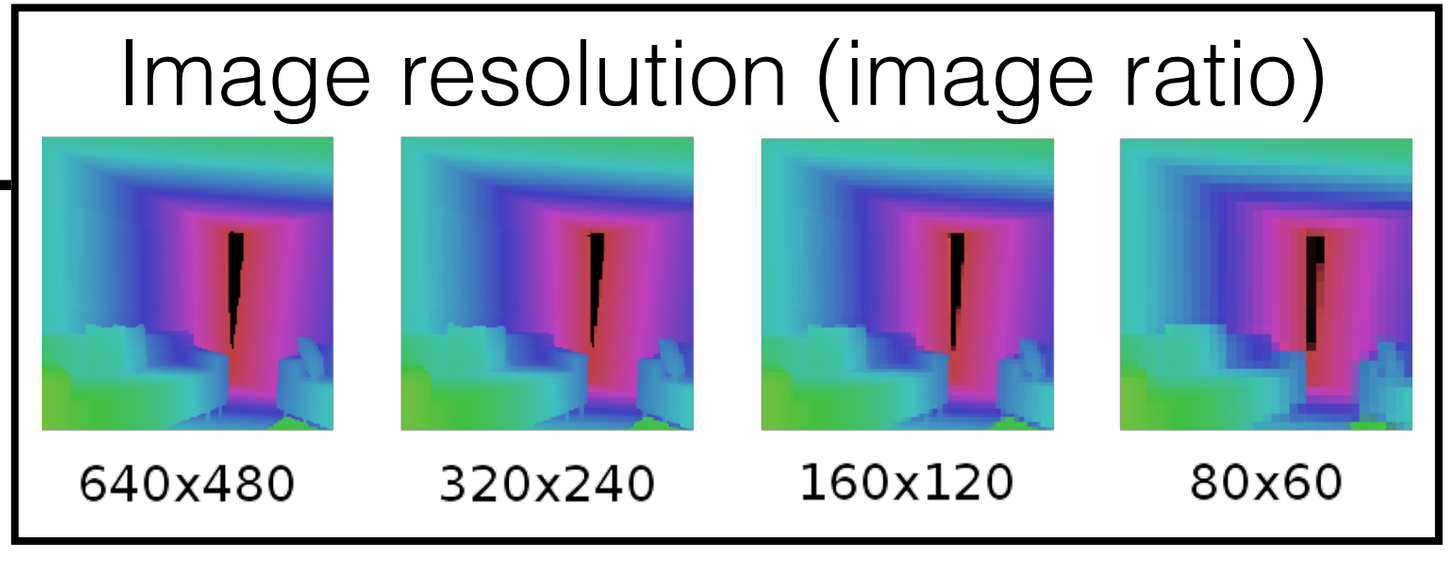

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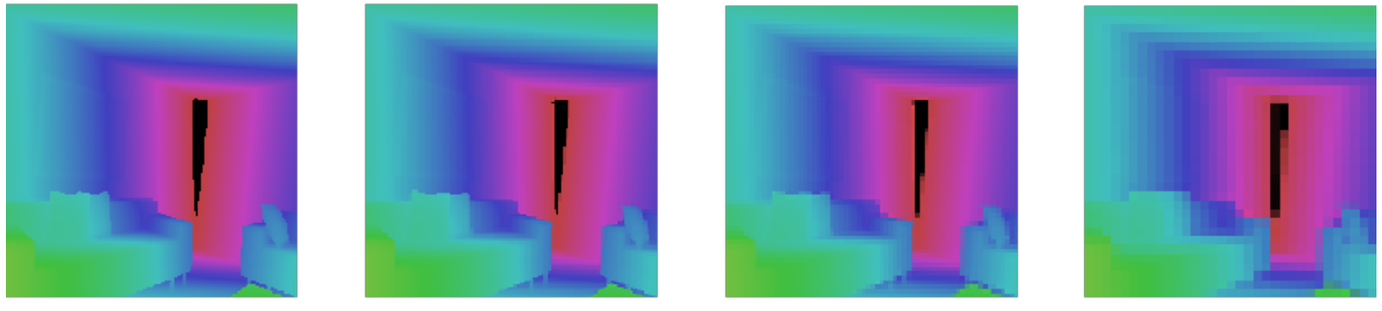
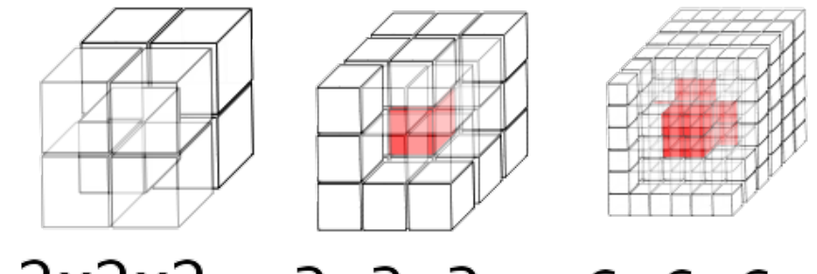
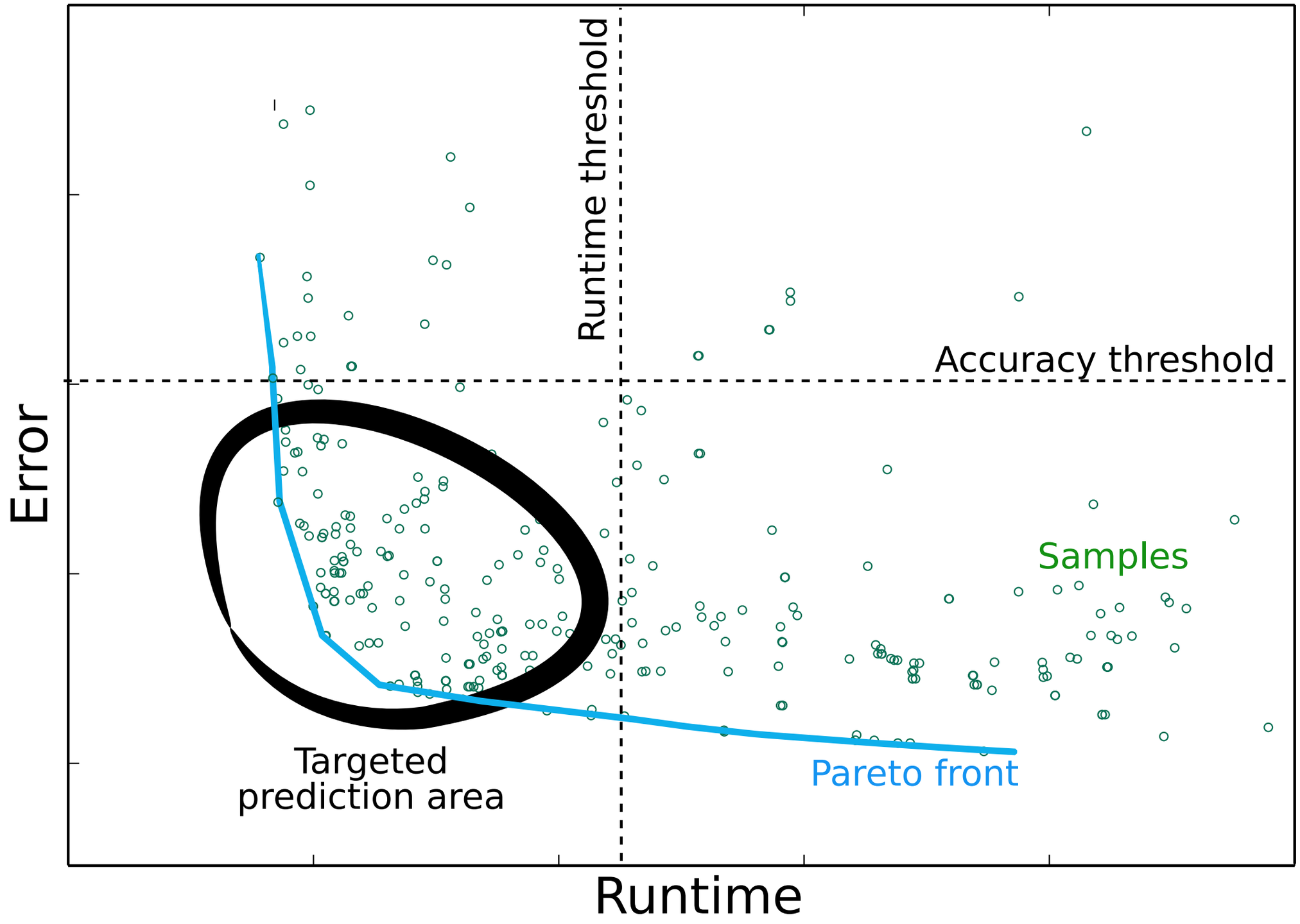


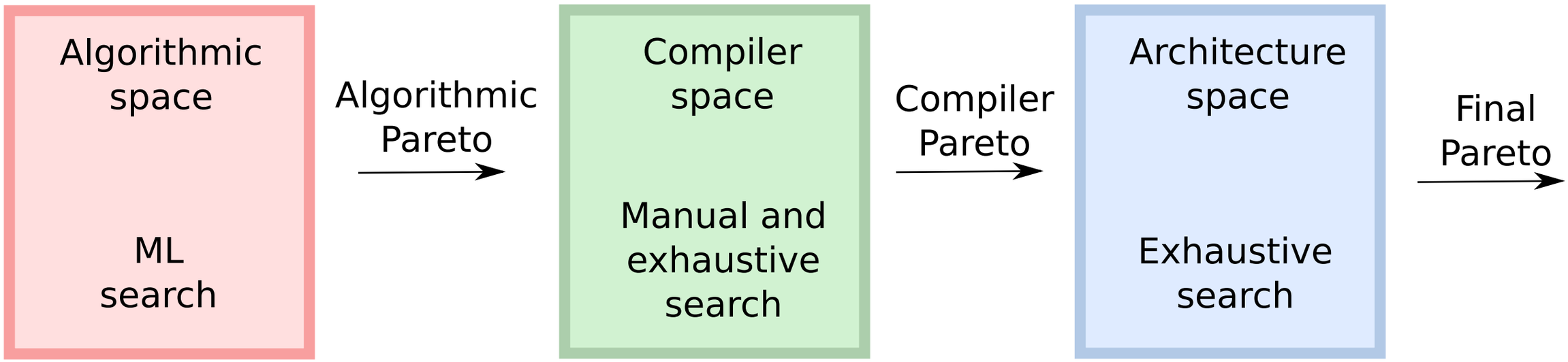
Volume resolution



Exploration goal



Incremental exploration approach

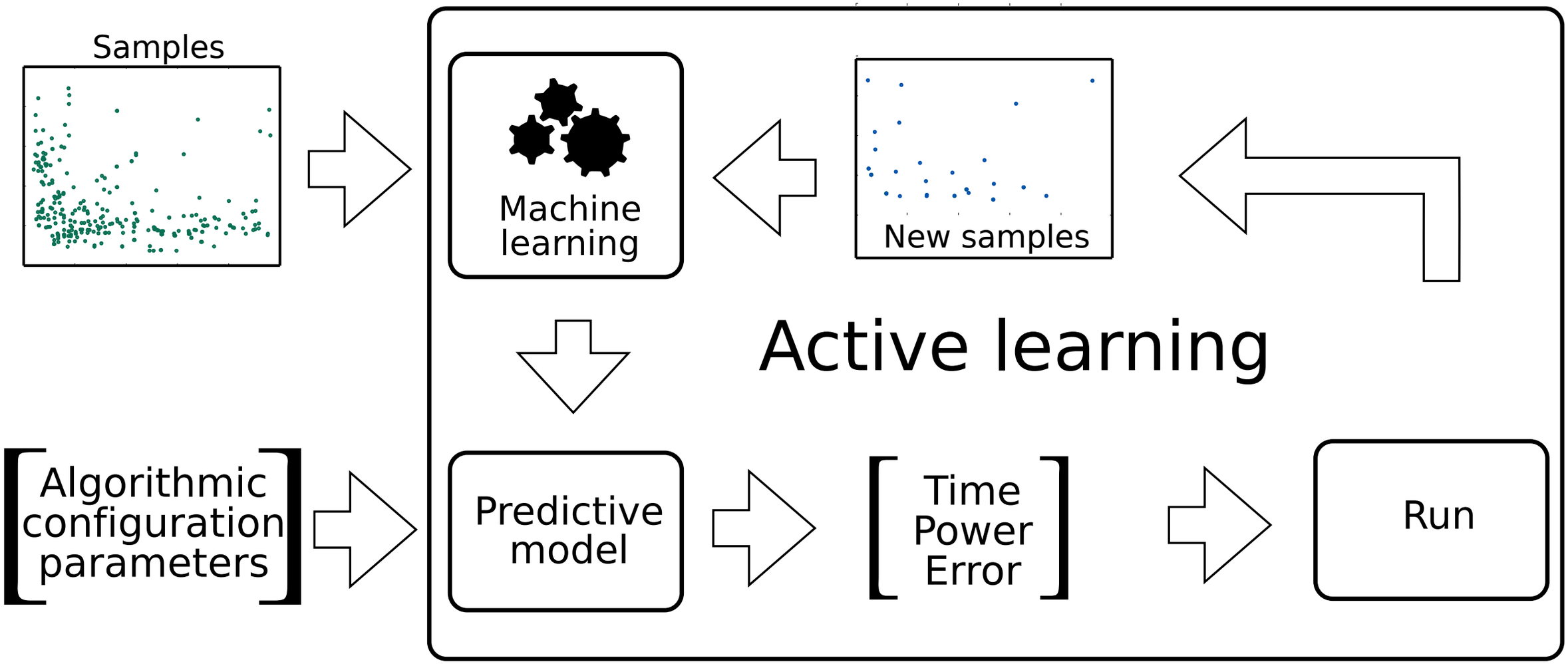


Frame rate
Power
Accuracy

Frame rate
Power
(Accuracy)

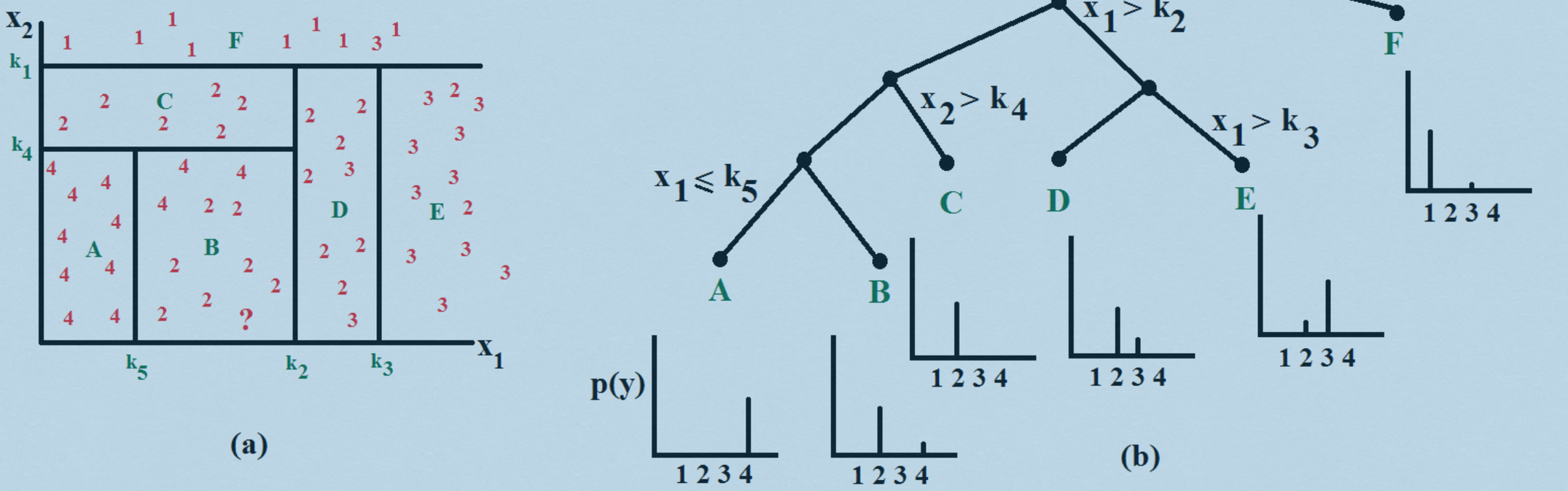
Frame rate
Power

Algo design-space exploration (DSE)

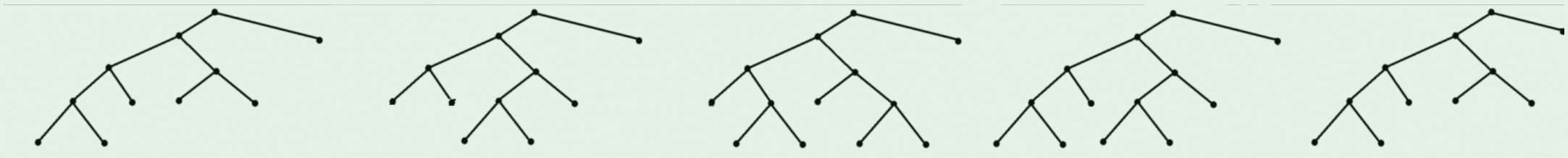


Machine learning methods used

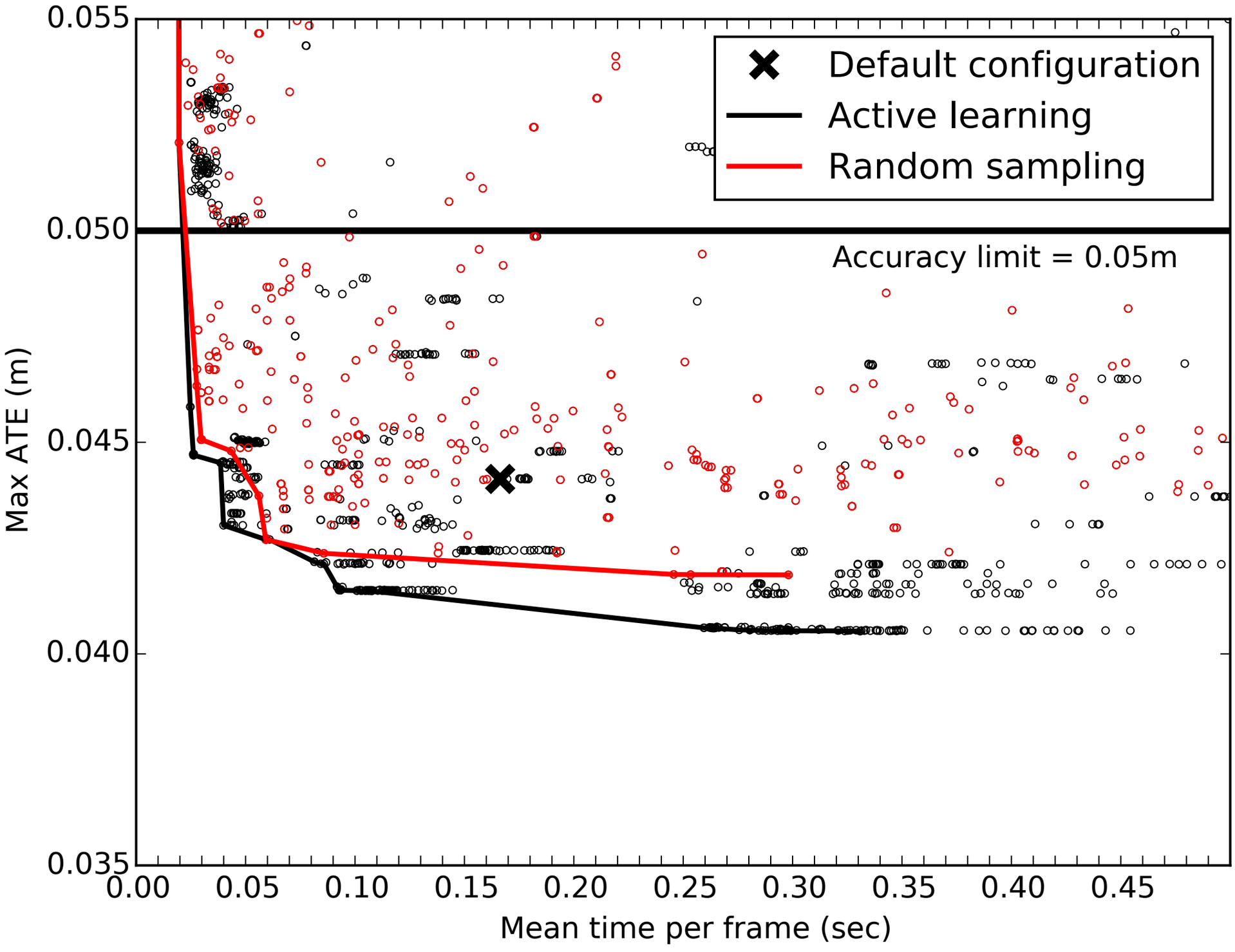
Decision tree



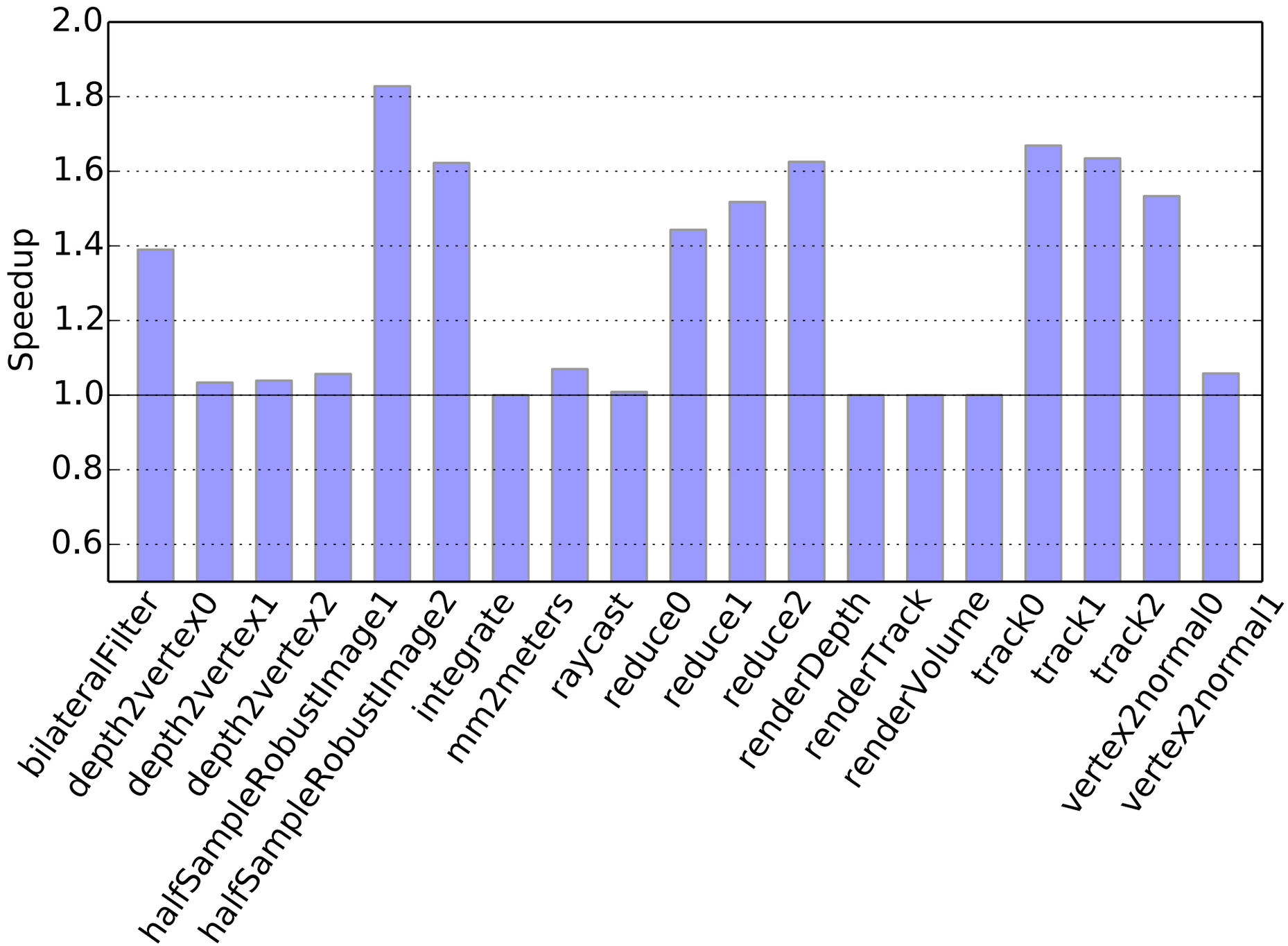
Random forest



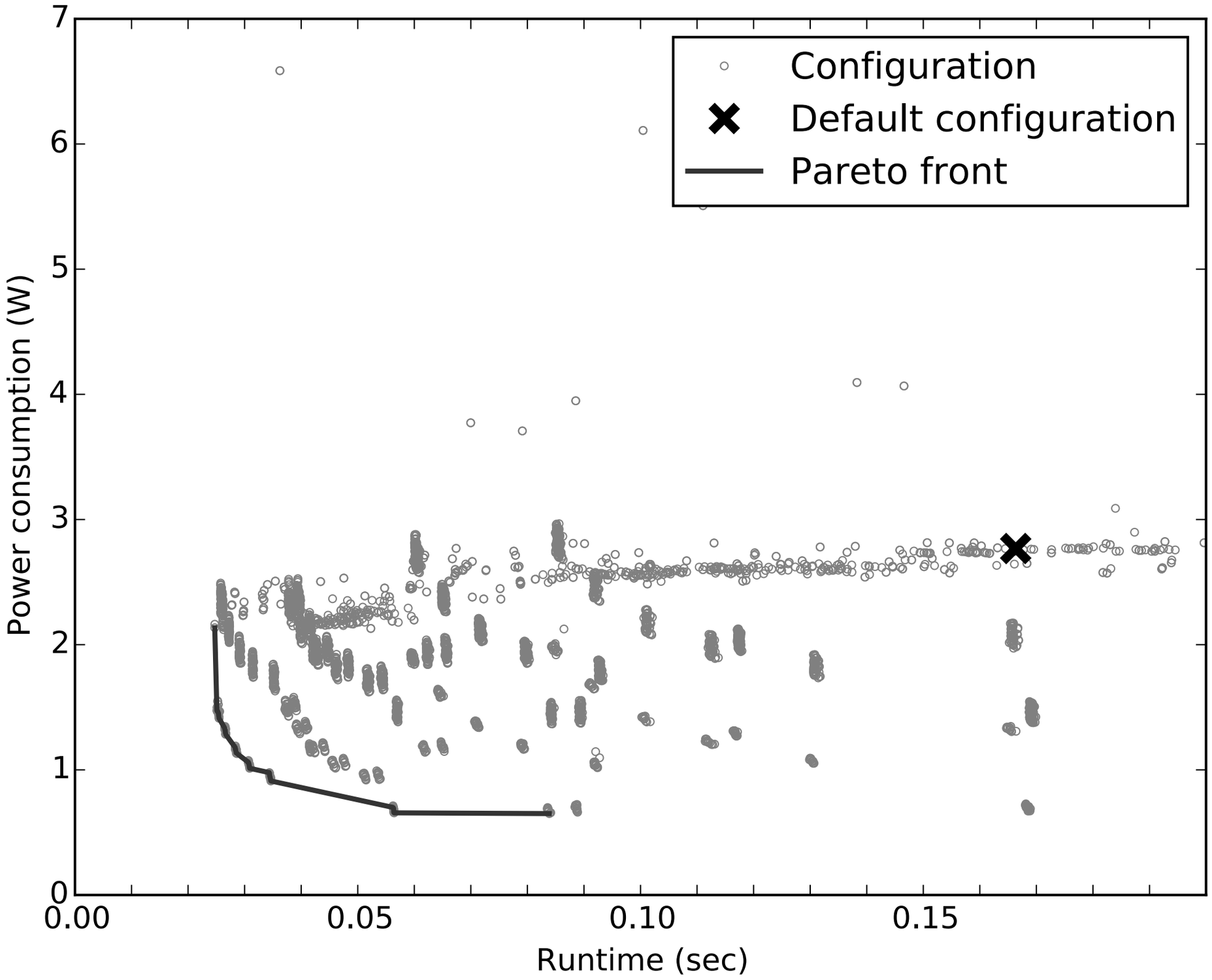
DSE on algorithmic parameters error/runtime



DSE compiler parameters speedup



DSE architecture parameters power/runtime

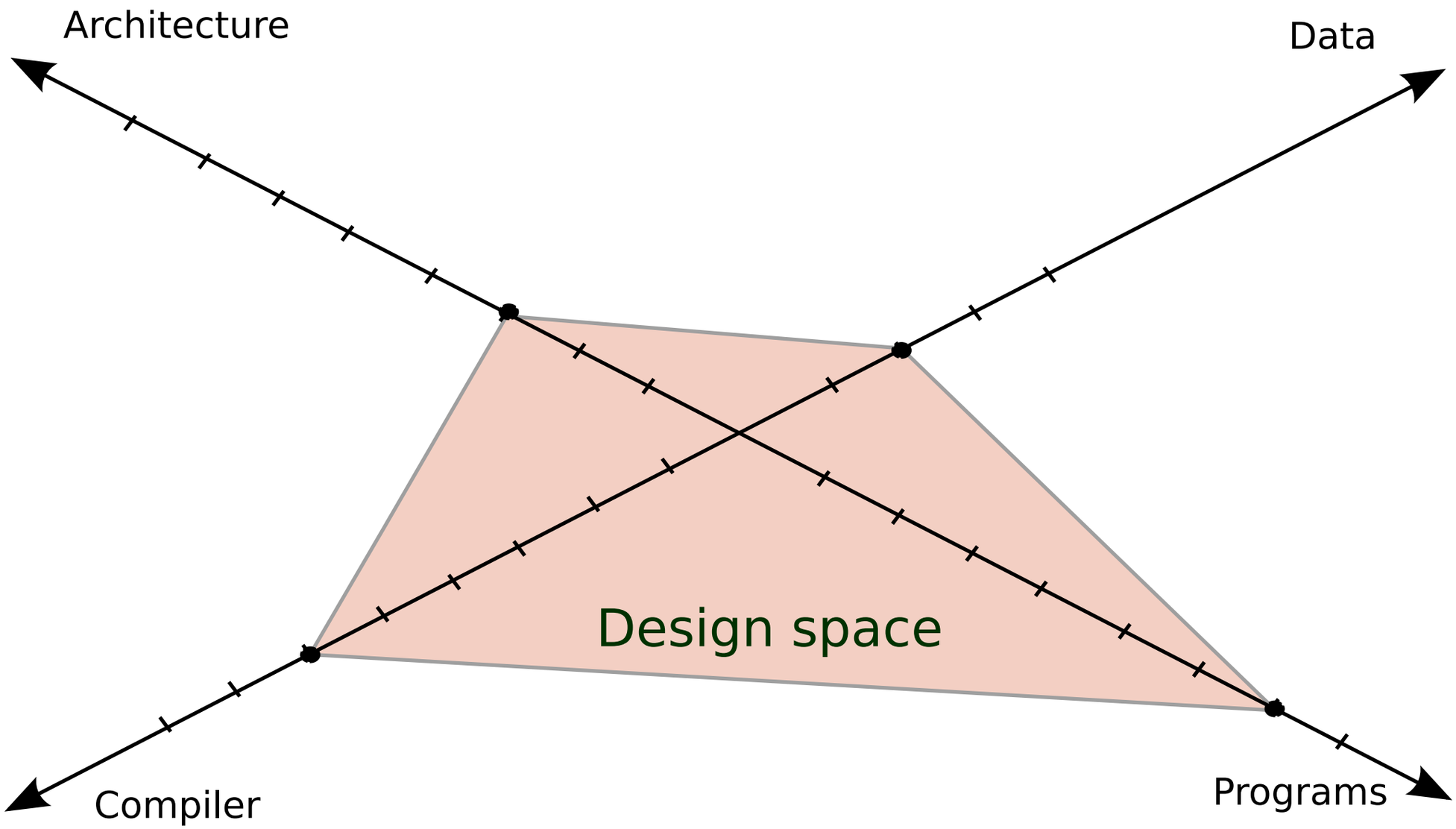


DSE final results and conclusion

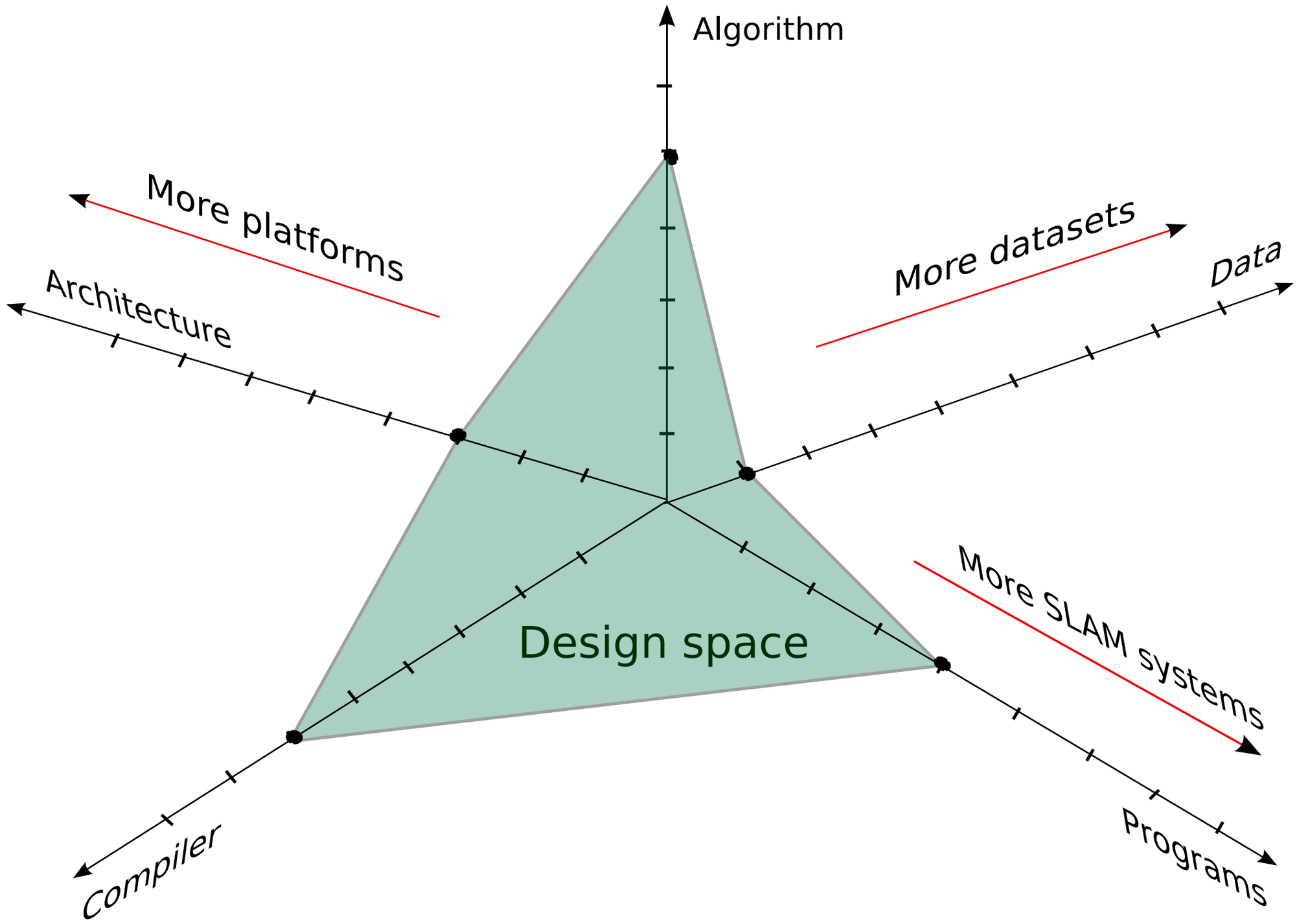
Constraint	Runtime (FPS)	Max ATE (cm)	Power (Watts)
Default	6.03	4.41	2.77
Best runtime	39.85	4.47	1.47
Best accuracy	1.51	3.30	2.38
Best power	11.92	4.45	0.65
Power $<$ 1W	29.09	4.47	0.98
Power $<$ 2W	39.85	4.47	1.47
FPS $>$ 10	11.92	4.45	0.65
FPS $>$ 20	28.87	4.47	0.91
FPS $>$ 30	32.38	4.47	1.01

- Multi-objective optimisation: frame rate/power/accuracy
- Auto-tuning tool to pick interesting points
- KinectFusion real-time on a popular embedded device
- Enabling auto-tuning at the domain-specific language (DSL) level

DSE the big picture I



DSE the big picture II



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