



1. INTRODUCTION: THE THREE R's OF COMPUTER VISION

Reconstruction

Scalable Kinect Fusion (2013)

Building Rome on a cloudless day (2010)

Recognition

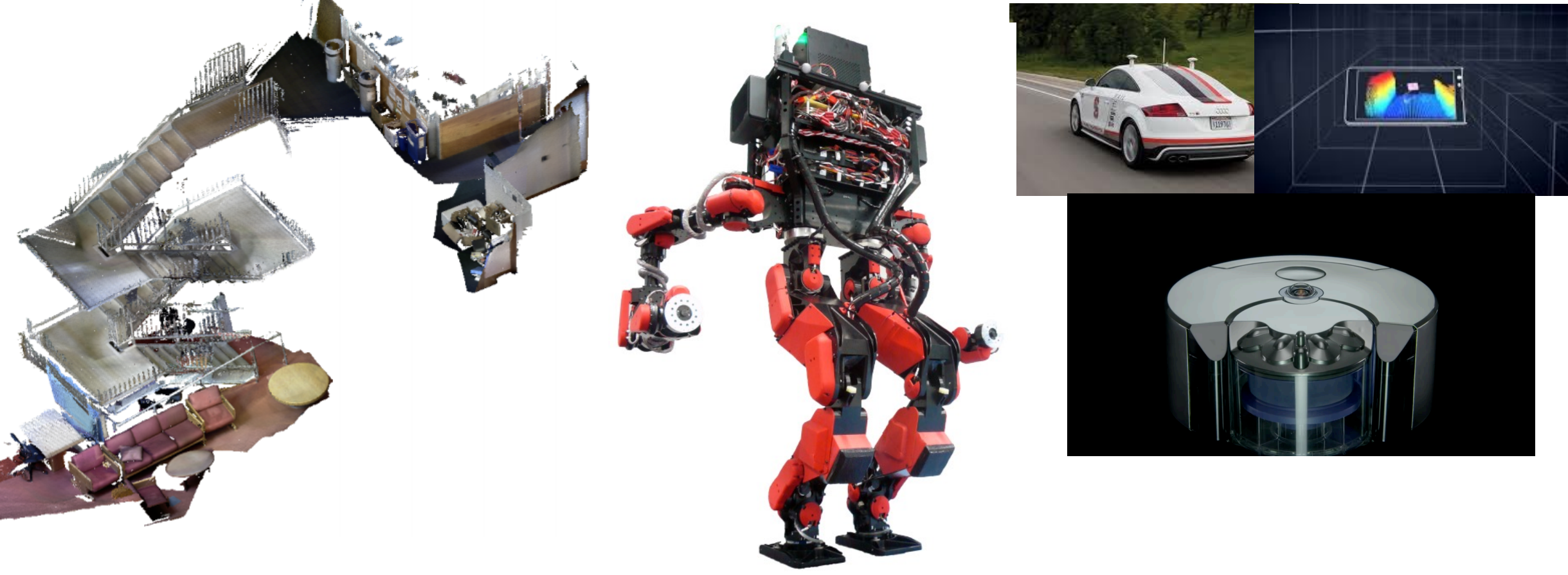
Deep learning for scalable Object class detection (2014)

Reorganisation or Grouping

Contour detection and segmentation (2011)

2. BACKGROUND: SIMULTANEOUS LOCALISATION AND MAPPING (SLAM)

We focus on the first "R": Reconstruction; more precisely in SLAM. SLAM builds a coherent world representation and localises the camera in real-time.



SLAMBench FRAMEWORK

Holistic approach to SLAM "performance": SLAMBench. SLAMBench is a publicly-available benchmarking framework for quantitative, comparable and validatable experimental research to investigate trade-offs in performance, accuracy and energy consumption of a SLAM system.

The accuracy is measured as Absolute Trajectory Error (ATE) in cm.

SLAM benchmarks

KinectFusion ... LSD-SLAM ... ORB-SLAM ...

Dense SLAM Semi-dense SLAM Sparse SLAM

Implementation languages

C++ OpenMP OpenCL CUDA SYCL PENCIL ...

Desktop to embedded platforms

ARM Intel NVIDIA ...

Datasets

ICL-NUIM TUM RGB-D ...

Performance evaluation

Frame rate Energy Accuracy

3. GOAL: MULTI-OBJECTIVE CO-DESIGN SPACE EXPLORATION

Space 1

Algorithmic:

- Application-specific parameters
- Minimisation methods
- Early exit condition values

Space 2

Compilation:

- openc1-params: -cl-mad-enable, -cl-fast-relaxed-math, etc.
- LLVM flags: O1, O2, O3, vectorize-slp-aggressive, etc.
- Local work group size: 16/32/64/96/112/128/256
- Vectorisation: width (1/2/4/8), direction (x/y)

Space 3

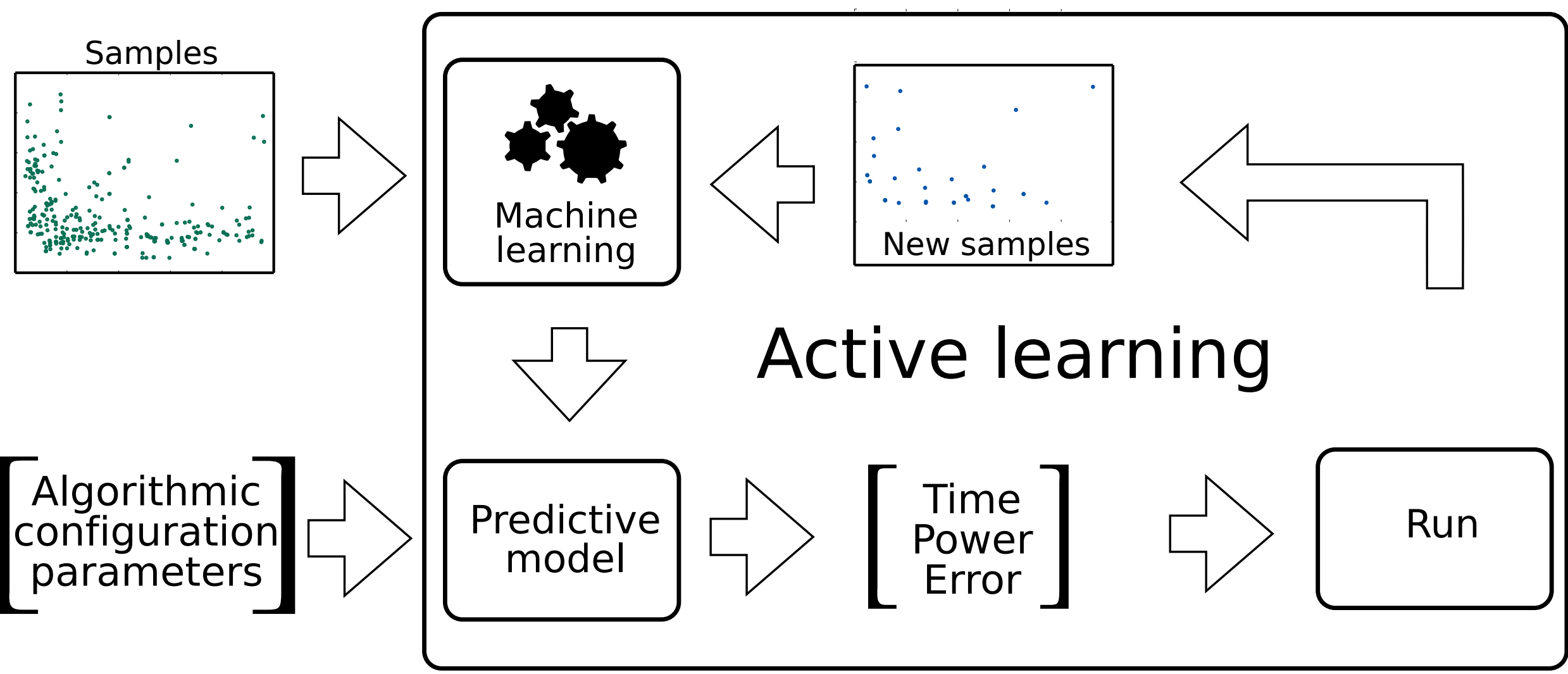
Architecture:

- GPU frequency: 177/266/350/420/480/543/600/DVFS
- # of active big cores: 0/1/2/3/4
- # of active LITTLE cores: 1/2/3/4

ACKNOWLEDGEMENTS

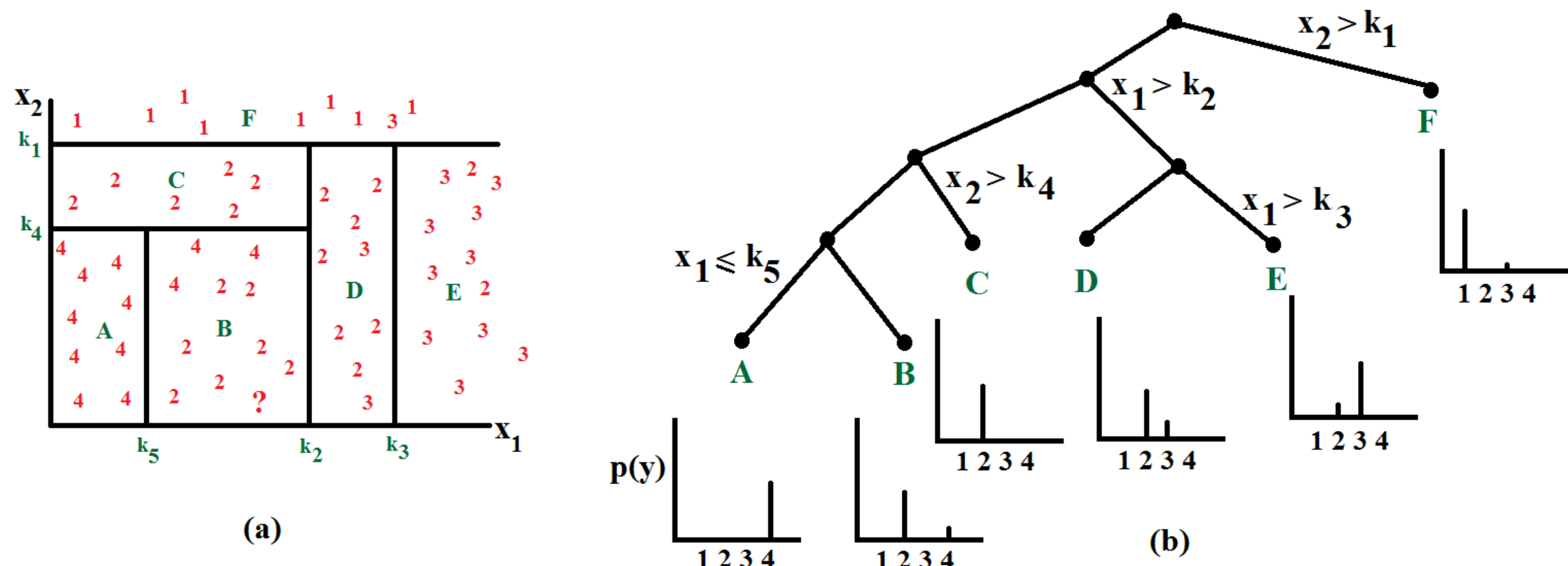
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4. METHOD: RANDOM FOREST AND ACTIVE LEARNING REGRESSION

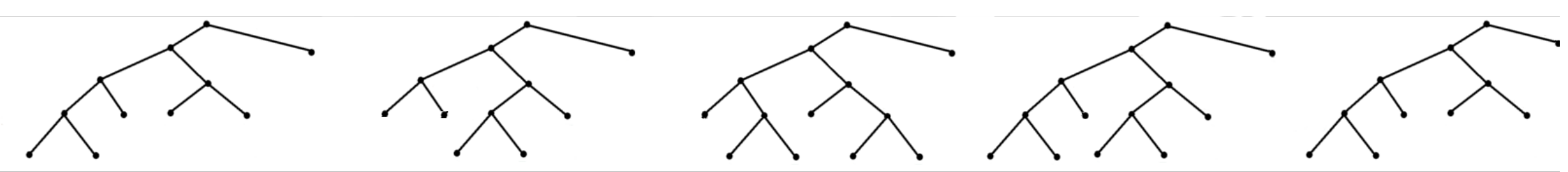


PREDICTIVE MODEL

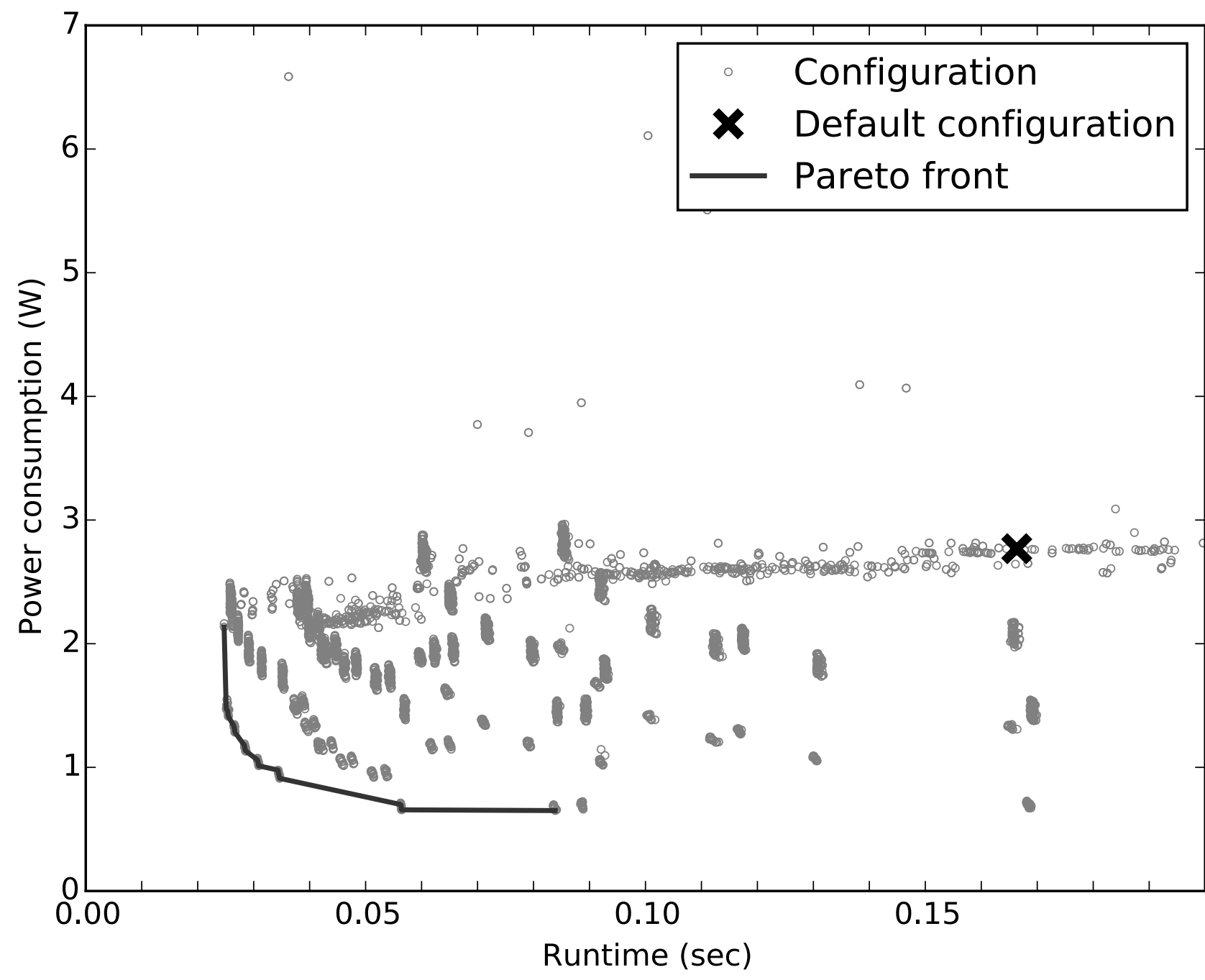
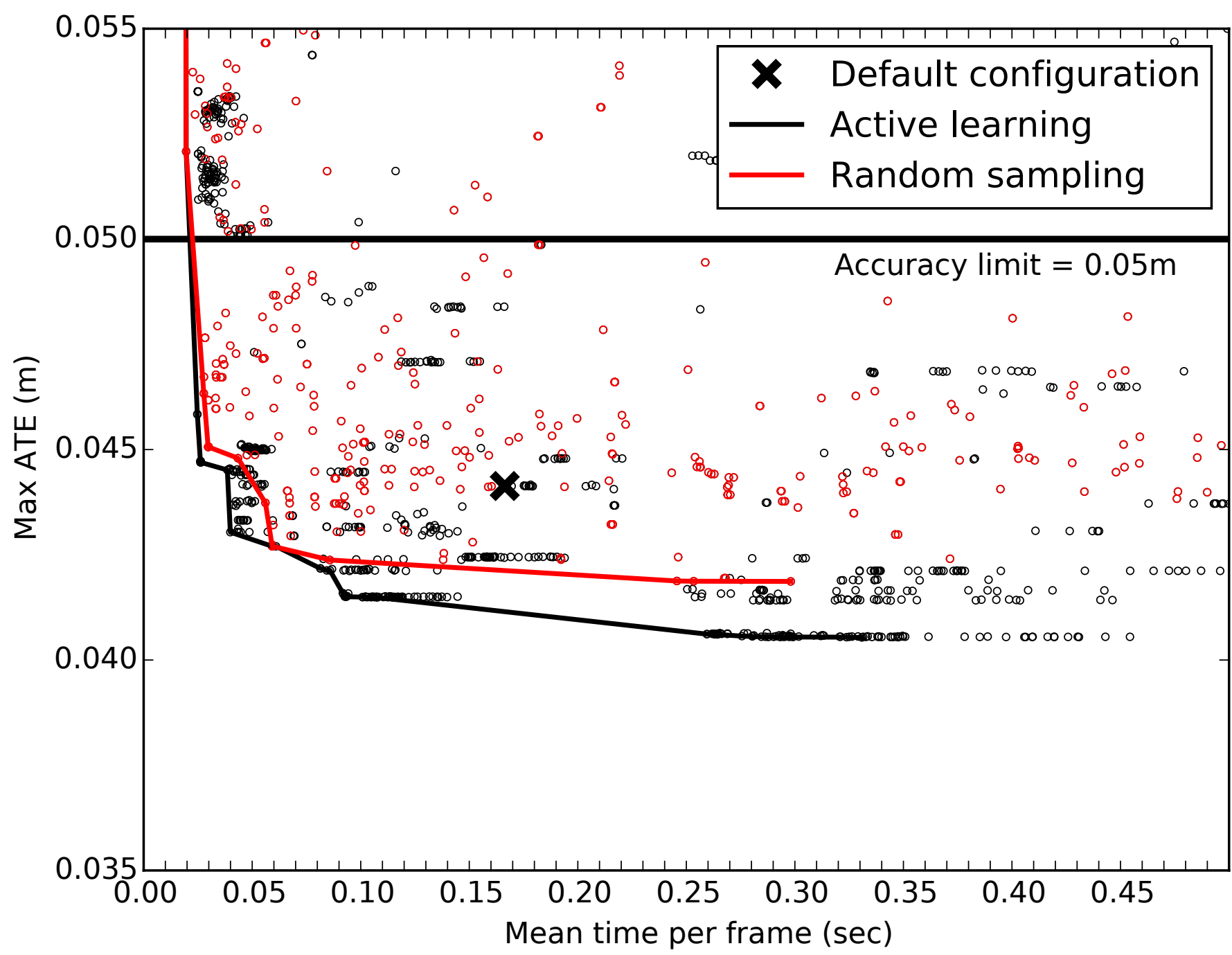
Decision tree



Random forest



5. RESULTS: PARETO SURFACE CONTAINING ALL OPTIMA FOUND



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



SELECTED PARETO POINTS

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

6. CONCLUSION

- Multi-objective machine learning driven optimisation framework on frame rate/power/accuracy brings us to find much better configurations than the default configuration.
- Application accuracy check very powerful: non bit-wise and scope for aggressive approximate computing.

REFERENCES

- M. Z. Zia, et al. Comparative Design Space Exploration of Dense and Semi-Dense SLAM. In IEEE ICRA, Stockholm, Sweden, May 2016.
- L. Nardi, et al. Introducing SLAMBench, a performance and accuracy benchmarking methodology for SLAM. In IEEE ICRA, Seattle, Washington USA, May 2015.

BIO: Luigi Nardi, PhD

Luigi Nardi is a Post-Doctoral Research Associate at Imperial College London in the Software Performance Optimisation group. Luigi's primary role is to work in the co-design of high-performance low-power computer vision systems where performance, power and accuracy are part of the same optimisation space. Prior to his current position, Luigi earned his Ph.D. in computer science at Pierre et Marie Curie University and was a permanent researcher leading the high-performance computing effort at Murex S.A.S.

