

High Performance Machine Learning Workshop



Energy Efficient K-Means Clustering for an Intel® Hybrid Multi-Chip Package

Matheus Souza, Lucas Maciel, Pedro Penna, Henrique Freitas

Agenda

- Introduction
- Background
 - K-Means Clustering and the CPU-FPGA platform
- Proposed Implementation
- Experimental Methodology
- Results and Conclusion

Introduction

Introduction

- The demand for HPC
 - Massively parallel architectures
 - Large-scale multi-cores
 - Challenge: Power consumption
- Heterogeneous computing
 - GPUs and Co-processors (Xeon Phi)
 - New challenge: data movement between devices
 - Big data scenario



Introduction

- Field Programmable Gate Arrays (FPGAs)
- Is FPGA a good alternative for Big Data processing
 - Runs specific tasks in hardware (no general purpose units)
 - K-Means implementations [3][4]
 - Offers 10% of GPUs' power consumption [5]
 - Scales better than CPU and GPU if used properly [6]

Introduction

- Challenge: Data movement between host and device
 - Low bandwidth
- Multi-chip Packaging (MCP) [7]
 - Integrates heterogeneous devices or chips in a single board
- Intel launched their MCP platform
 - Xeon Broadwell CPU + Arria 10 FPGA

Introduction

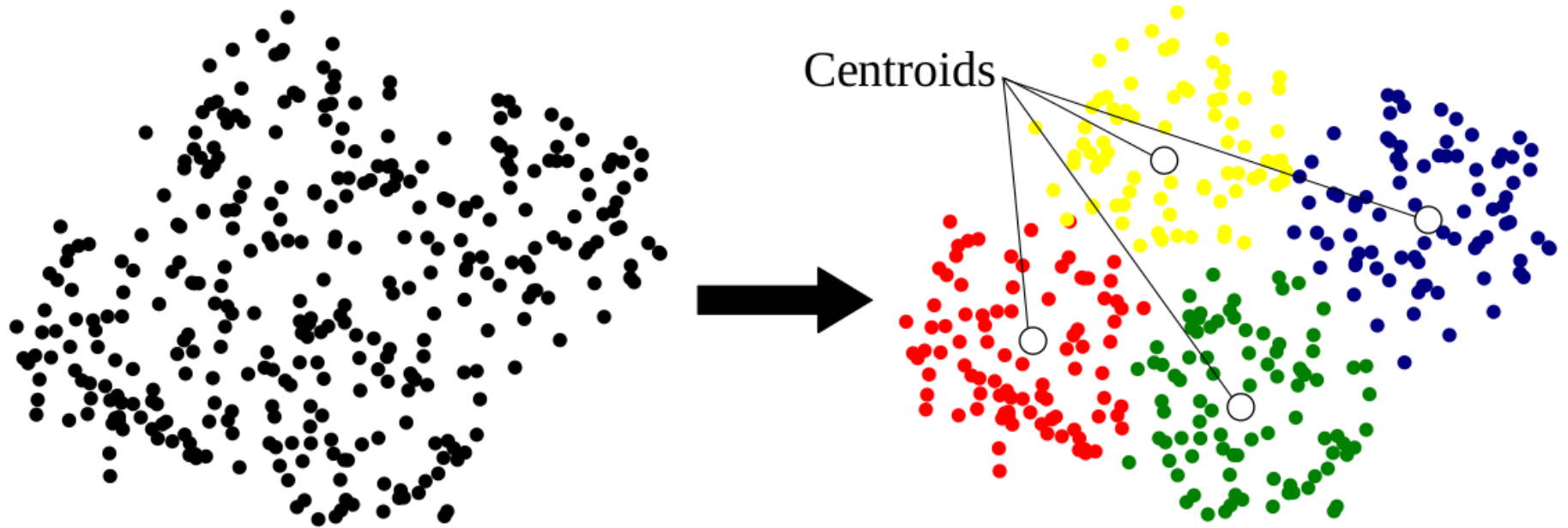
- Back to Big Data
 - Consider the ever growing amount of data to be processed
 - Can hybrid MCPs accelerate Machine Learning applications?
- Our goal is to propose and evaluate K-Means algorithm for the Intel Broadwell + Arria 10 platform
- Contributions
 - OpenCL-based implementation for the novel platform
 - Comparative analysis against other platforms

Background

Background: K-Means Clustering

- Unsupervised Machine Learning algorithm
- Partition and group data according to their features
- Euclidean distance
- Given:
 - A set of n data points
 - A real d -dimensional space
 - k -clusters

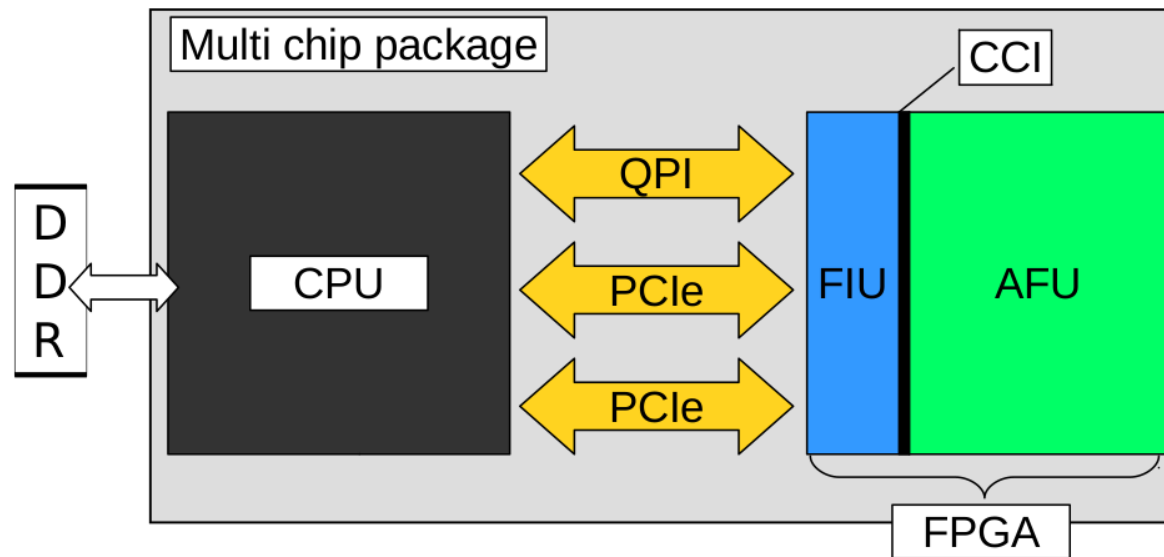
Background: K-Means Clustering



Background: CPU-FPGA platform

- Intel hybrid MCP
 - Host:
14-core Xeon Broadwell @ 2.4GHz
 - Device:
Arria 10 FPGA, GX1150
 - Interconnection:
2 PCIe (16 GB/s together)
1 QPI (12.8 GB/s)

Background: CPU-FPGA platform



- FIU: FPGA Interface Unit
- AFU: Accelerated Function Unit
- CCI: Core Cache Interface
 - Communication done in a coherent manner

Proposed Parallel K-Means

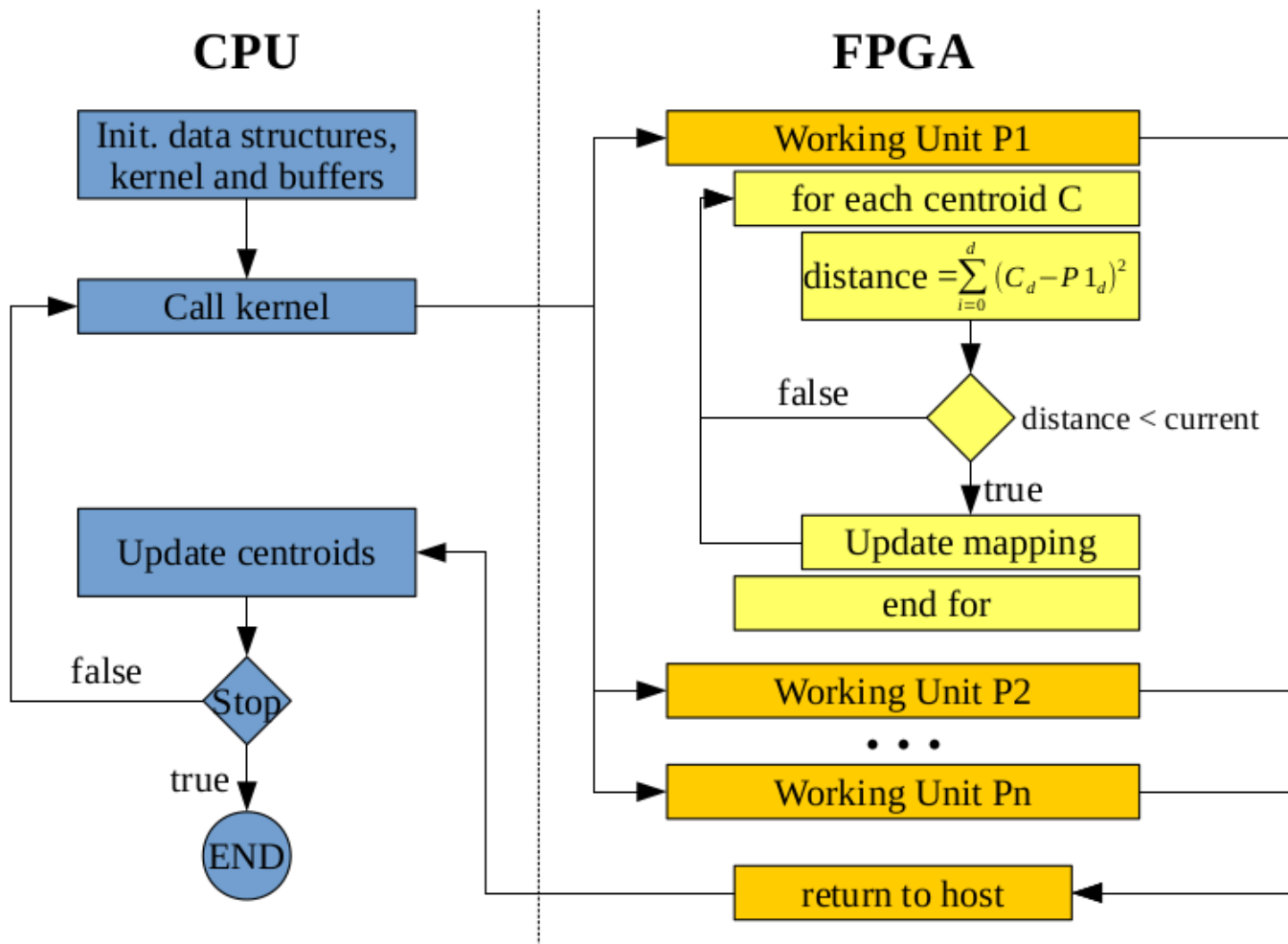
Proposed Parallel K-Means

- Baseline: OpenMP version from CAP Bench [17]
 - A benchmark suite for performance and energy evaluation of low-power many-core processors
- Intel hybrid and heterogeneous MCP platform

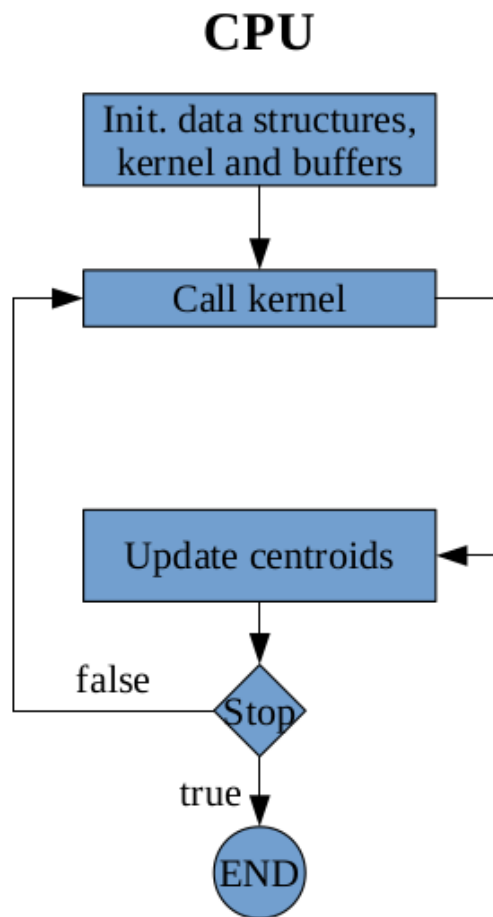
Host: C/C++ code to initialize the system, data structures and for synchronization

Device: OpenCL kernel to perform the desired computation

Proposed Parallel K-Means



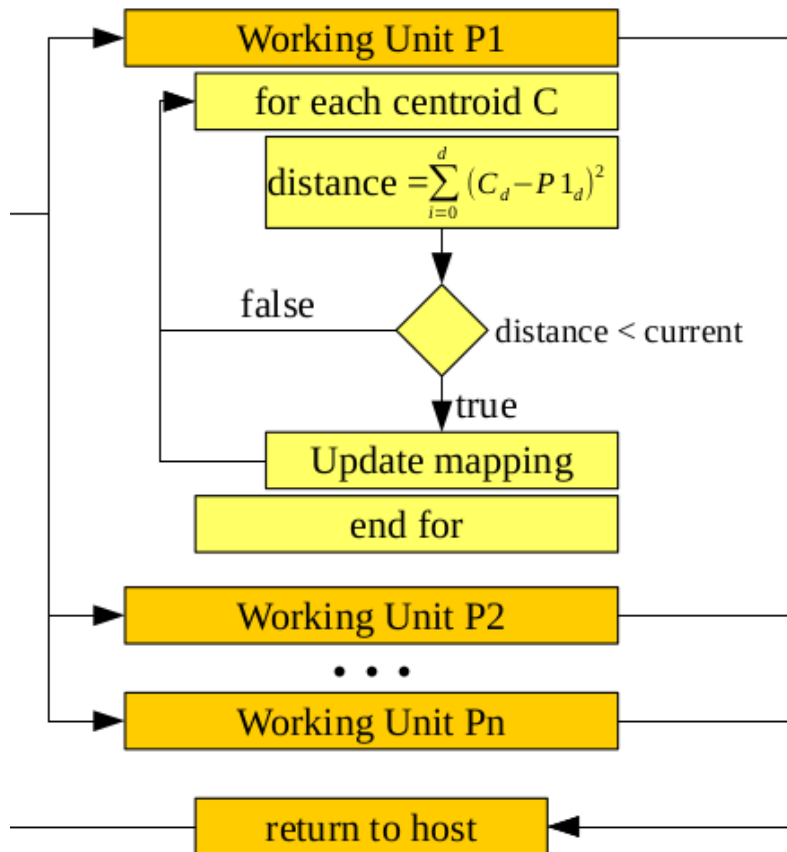
Proposed Parallel K-Means



- Update centroids at the host (C/C++)
 - Not much complex arithmetic operations
 - Conditional branches (not suitable for the FPGA)
 - Data movement (only centroids need to be offloaded)
 - OpenMP using 14-cores

Proposed Parallel K-Means

FPGA



- Distance computing using *NDRange Kernel*
- No gains when using *SimpleTask* pipeline
- High data parallelism (no dependency between data points)
- Number of *Working Units* equal to the amount of data points

Proposed Parallel K-Means

- Square root from Euclidean distance removed
 - Does not change the point-to-centroid mapping
- Loop unroll for features
 - Features are independent from each other at the first step of the Euclidean distance

Experimental Methodology

Experimental Methodology

- Compilers and tools
 - Intel SDK for OpenCL compiler (AOCL)
 - Quartus 16.0.2 (Power Play included)
 - GCC 4.9.2 (OpenMP 4.0)
 - PAPI (for measuring CPU energy consumption)

Experimental Methodology

- Other platforms
 - CPU: Intel Xeon Sandy Bridge E5-2620 (12 cores @ 2.10 GHz)
 - Intel Xeon Phi Knights Corner (61 cores)
 - 8-node Raspberry Pi B2 cluster (32 cores)
 - Kalray MPPA-256 many-core (256 cores)
- 20 tests (standard error lower than 8%)

Experimental Methodology

- Workload sizes

Workload	Data points	Centroids	Features	Iterations*
Tiny	4096	256	16	13
Small	8192	512	16	15
Standard	16384	1024	16	14
Large	32768	1024	16	25
Huge	65536	1024	16	48

* Measured after the tests

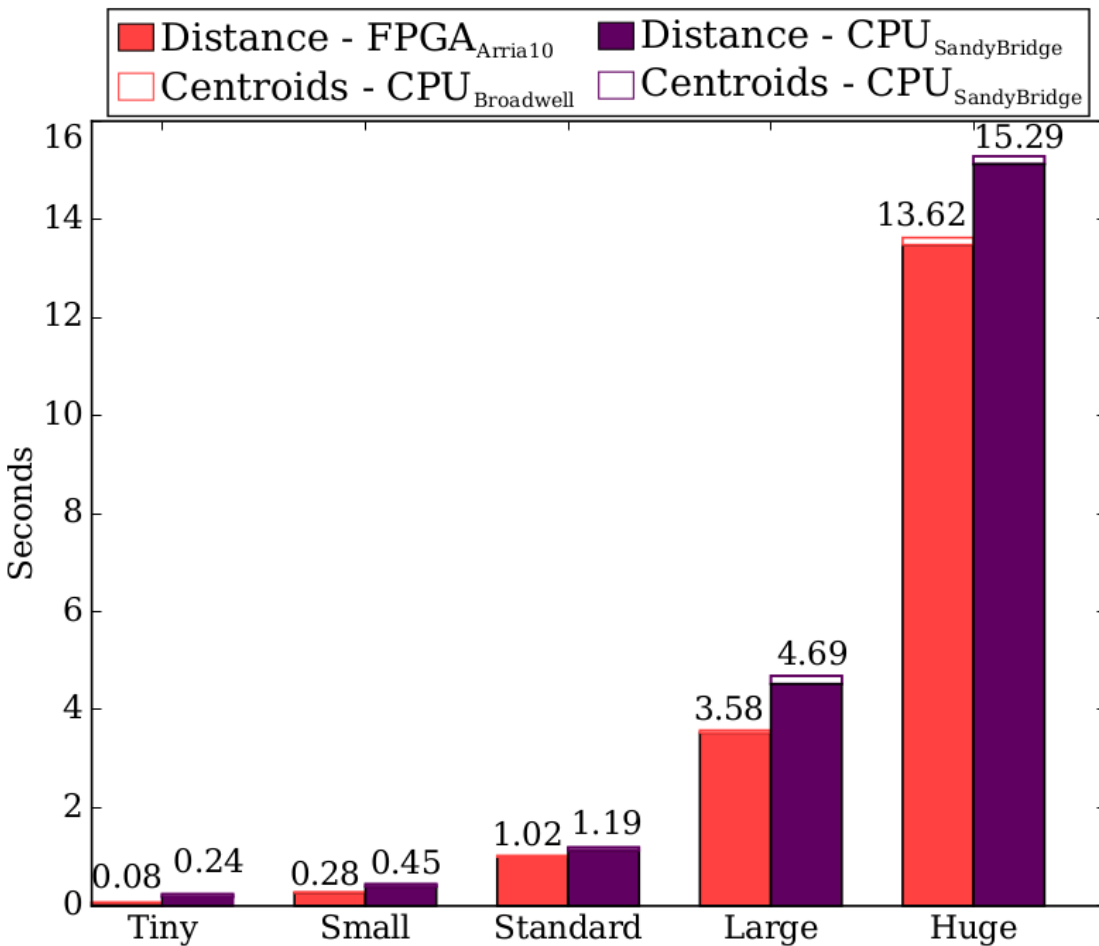
Results Evaluation

Results: Resource usage

Resource	Available	AFU
Logic utilization	1150	10% (115)
ALUTs	427200	4% (17088)
Registers	1708800	6% (102528)
Memory blocks	67244	12% (8069)
DSP blocks	1518	5% (76)

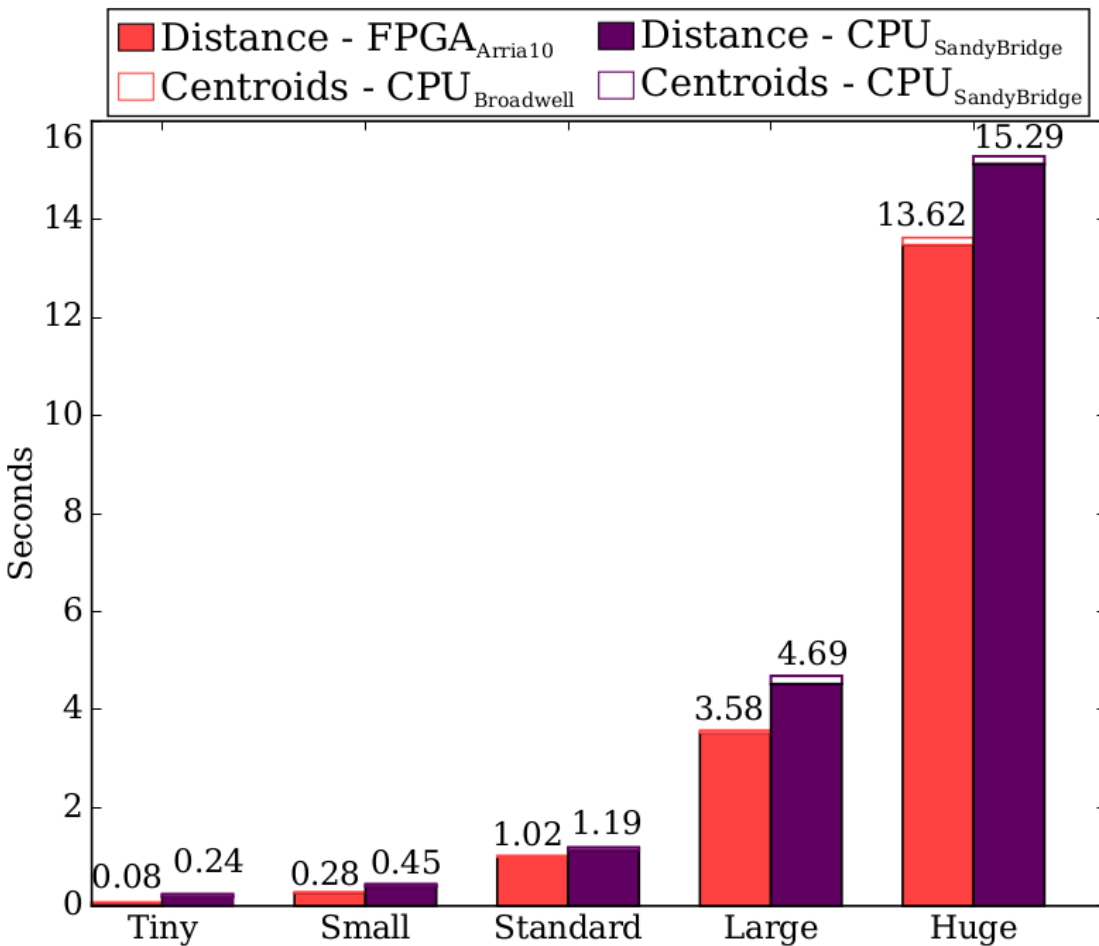
- There is still space for other kernels

Results: Time to solution



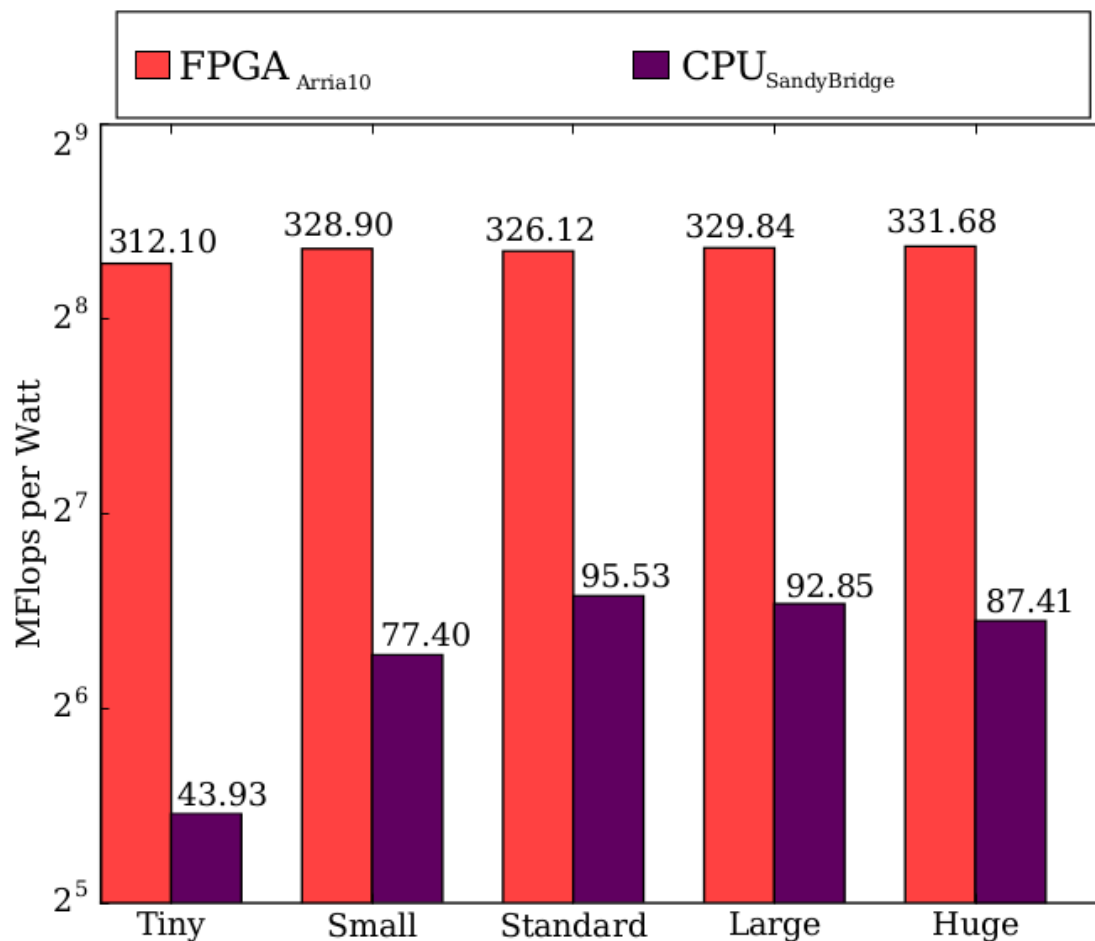
- Centroids computing does not represent much
- Read/write to/from host/device represent, at most, 1.22% from overall time
- Time increases proportionally to input sizes and iterations
- CPU scales slightly better, however, the FPGA is faster.

Results: Time to solution



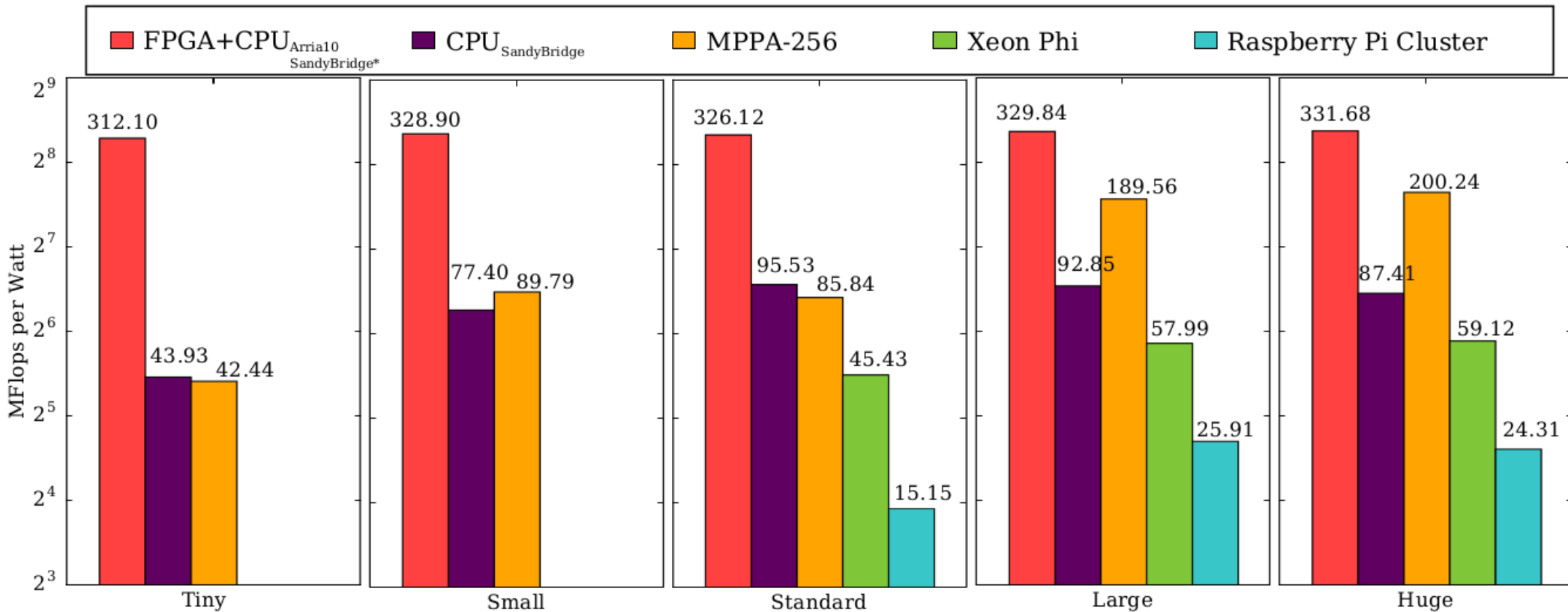
- FPGA improvements:
 - Tiny: 68.21%
 - Small: 36.57%
 - Standard: 14.03%
 - Large: 23.59%
 - Huge: 10.82%

Results: Energy efficiency



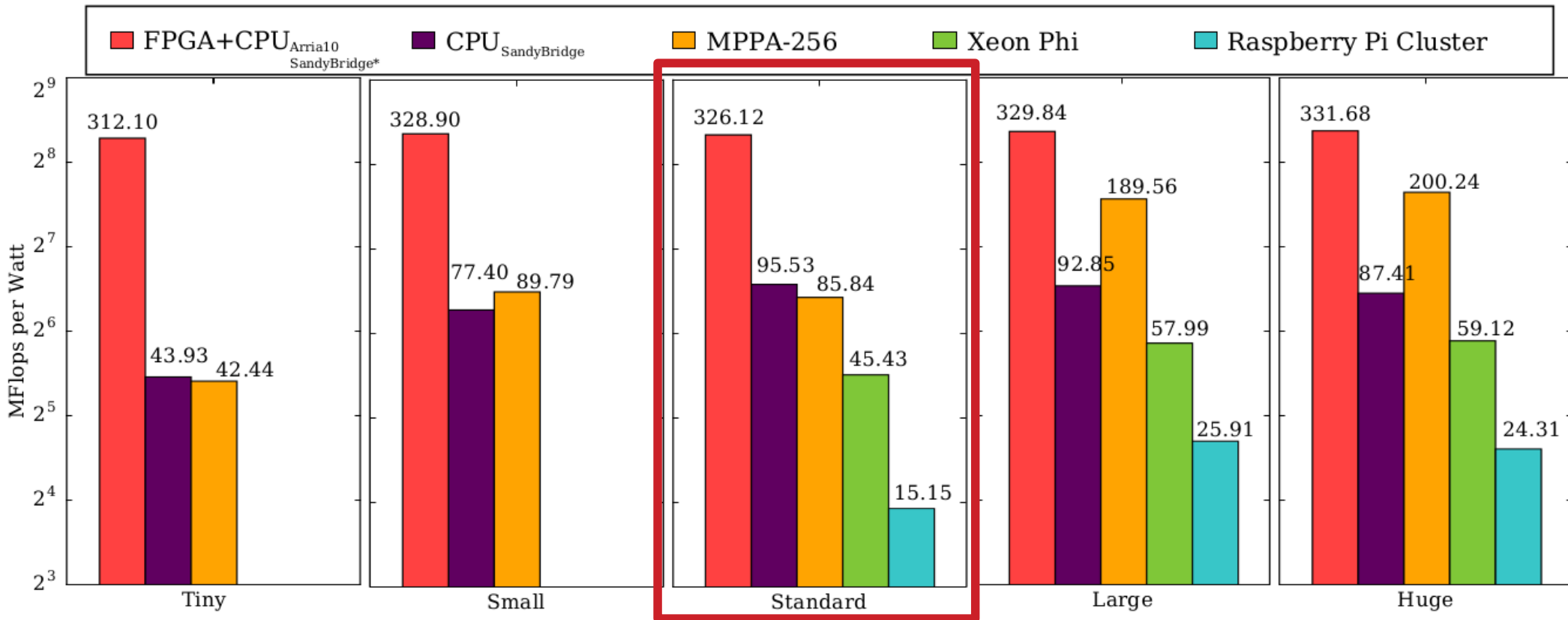
- Tiny to Standard: CPU improves efficiency, but it starts to decrease with higher inputs
- CPU+FPGA is more energy efficient than the CPU
 - FPGA consumes less power
- Improvements:
 - Lowest: 70.71% (Standard)
 - Biggest: 85.92% (Tiny)

Results: Other platforms



- **Xeon Phi:** CPU+FPGA is 7.2x more energy efficient
- **Raspberry Cluster:** CPU+FPGA is 21.5x more energy efficient
- **Kalray MPPA-256:** CPU+FPGA is 3.8x more energy efficient

Results: Other platforms



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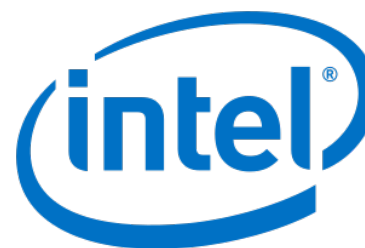
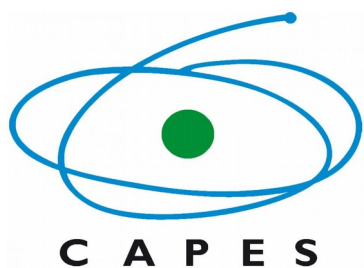
Conclusion

- Energy efficiency evaluation of K-Means
- Novel Intel hybrid MCP platform
 - Xeon Broadwell CPU + Arria 10 FPGA
- Up to 85.92% more energy efficient than CPU-only
- More energy efficient than other platforms

Future work

- Further K-Means evaluations
 - Real datasets
 - Other platforms (e.g. GPU)
- Other Machine Learning algorithms
 - Deep Neural Networks
 - Support Vector Machines
 - Decision Trees
- Load balance considering the system heterogeneity

Acknowledgement



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Related Work

Related Work

- FPGA-based solutions for Deep Neural Networks
 - Memory restrictions: key problems
- Stream buffers to reduce data exchange [18]
- Pipeline of kernels to increase data reuse [19]
- Floating point precision reduction [20]

Related Work

- K-Means clustering
 - Hardware implementations vs. software ones
- Single FPGA: 95% less energy consumption [4]
- Single FPGA: Speedup of 10x [22]
- Multiple FPGAs: Speedup of 330x [24]

References

- [3] Q. Y. Tang et al: Acceleration of k-Means Algorithm Using Altera SDK for OpenCL
- [4] L. A. Maciel et al: Projeto e Avaliação de uma Arquitetura do Algoritmo de Clusterização K-Means em VHDL e FPGA
- [5] J. Cong et al: Understanding performance differences of FPGAs and GPUs
- [6] K. O'Brien et al: Towards exascale computing with heterogeneous architectures
- [7] R. Tummala et al: Heterogeneous and homogeneous package integration technologies at device and system levels
- [17] M. A. Souza et al: CAP Bench: a benchmark suite for performance and energy evaluation of low-power many-core processors
- [18] U. Aydonat et al: An OpenCL deep learning accelerator on Arria 10
- [19] D. Wang et al: PipeCNN: An OpenCL-based FPGA accelerator for large-scale convolution neuron networks
- [20] J. Zhang et al: Improving the performance of OpenCL-based FPGA accelerator for convolutional neural network
- [22] J. Canilho et al: Multi-core for K-means clustering on FPGA
- [24] M. Vidal et al: Implementation of the K-means algorithm on heterogeneous devices: a use case based on an industrial dataset

Background: K-Means Clustering

```
1: procedure KMEANS( $k$ , points,  $d$ )
2:   centroids  $\leftarrow$  random_centroids( $k$ , points,  $d$ )
3:   repeat
4:     map  $\leftarrow$  compute_distances(points, centroids,  $d$ )
5:     recalculate_centroids(points, centroids, map,  $d$ )
6:   until not check_if_should_stop()
7:   return map
8: end procedure
```

Results: Resource usage

Resource	Available	FIU + CCI	AFU
Logic utilization	1150	49% (563)	10% (115)
ALUTs	427200	23% (98256)	4% (17088)
Registers	1708800	27% (461376)	6% (102528)
Memory blocks	67244	23% (15466)	12% (8069)
DSP blocks	1518	12% (182)	5% (76)

- FIU + CCI consume a considerable resources
- There is still space for other kernels