



# Three is not a crowd

## A CPU-GPU-FPGA K-means implementation

Borja Pérez Pavón

University of Cantabria

Carlos Escuín Blasco

Polytechnic University of Catalonia

Denisa-Andreea Constantinescu

University of Malaga

Jorge Cáncer Gil

University of Zaragoza

Marcos Canales Mayo (team leader)

University of Zaragoza

# The team



**Borja**

**University of  
Cantabria**



**Carlos**

**Polytechnic  
University of  
Catalonia**



**Jorge**

**University of  
Zaragoza**



**Marcos**



**Denisa**

**University of  
Malaga**

# Table of contents

## Intro

- Problem description
- Study of existing implementations

## Our strategy

- Available platforms
- Implementation decisions

## Implementation

- OpenMP
- FPGA + CPU
- (2x)GPU + CPU
- FPGA + CPU + (2x)GPU

## Overall results

- Methodology
- Test results
- Conclusions



# 1.Intro

**Problem description**

**Study of existing implementations**

# Problem description

## Definitions

- ▶ **Clustering:** task of assigning a set of objects into groups.
- ▶ **k-means clustering:**
  - ▶ method of clustering
  - ▶ partition  $n$  data points into  $k$  clusters ( $n \gg k$ )
  - ▶ each point belongs to the cluster with the **nearest** mean.
- ▶ The **nearness:** usually Euclidean or Manhattan distance.
- ▶ **Assumption:** data points are independent of each other.

# Problem description

## The algorithm

**Input:** set of  $N$  points with  $D$  dimensions  
 $K$  (number of clusters)

**Output:** partition of  $N$  points in  $K$  clusters

1. Place centroids  $c_1, c_2, \dots, c_K$  at random locations
2. Iterate until convergence condition is met
3. For each point  $x_i, i=1..N$ :
4.     For each cluster  $c_j, j=1..K$ :
5.         Get distance to  $c_j$ , given all  $D$  dimensions
6.         Assign membership of  $x_i$  to nearest cluster  $j$
7. For each cluster  $c_j, j=1..K$ :
8.      $c_j =$  mean of all points whose membership is  $j$

$O(\#iterations \times N \times D \times K)$

# Study of existing implementations

Implementation	Approach	Device
1. Rodinia	OpenMP	CPU
	OpenCL	GPU
	CUDA	GPU
2. OpenDwarfs	OpenCL	CPU   GPU FPGA   MIC
3. NU-MineBench	OpenMP	CPU
4. Hetero-Mark	OpenCL	CPU   GPU
5. CyberPoint	MPI	CPUs

## Web references:

1. <https://www.cs.virginia.edu/~skadron/wiki/rodinia/index.php/K-Means>
2. <https://github.com/vtsynergy/OpenDwarfs>
3. <http://cucis.ece.northwestern.edu/projects/DMS/MineBenchDownload.html>
4. <http://www.ece.neu.edu/groups/nucar/software/hetero-mark/>
5. <https://github.com/CyberPoint/libem>



# 2. Our strategy

Available platforms

Implementation decisions



# Available platforms

▶ Intel® Core™ i7-6700K



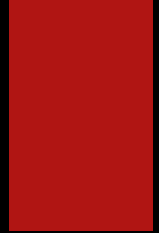
▶ 2 x NVIDIA TITAN X



▶ Altera Terasic Stratix V  
DE5-NET FPGA



# Implementation decisions



- ▶ **Considerations:**
  - ▶ Points don't change between iterations. They need to be distributed only once among devices.
  - ▶ The application is regular
- ▶ **Rodinia OpenCL** as a starting point
  - ▶ GPU focused.
  - ▶ Develop a kernel tuned for the FPGA
- ▶ **CPU**
  - ▶ Just update centroids and control convergence



# 3. Implementation

FPGA + CPU

(2x)GPU + CPU

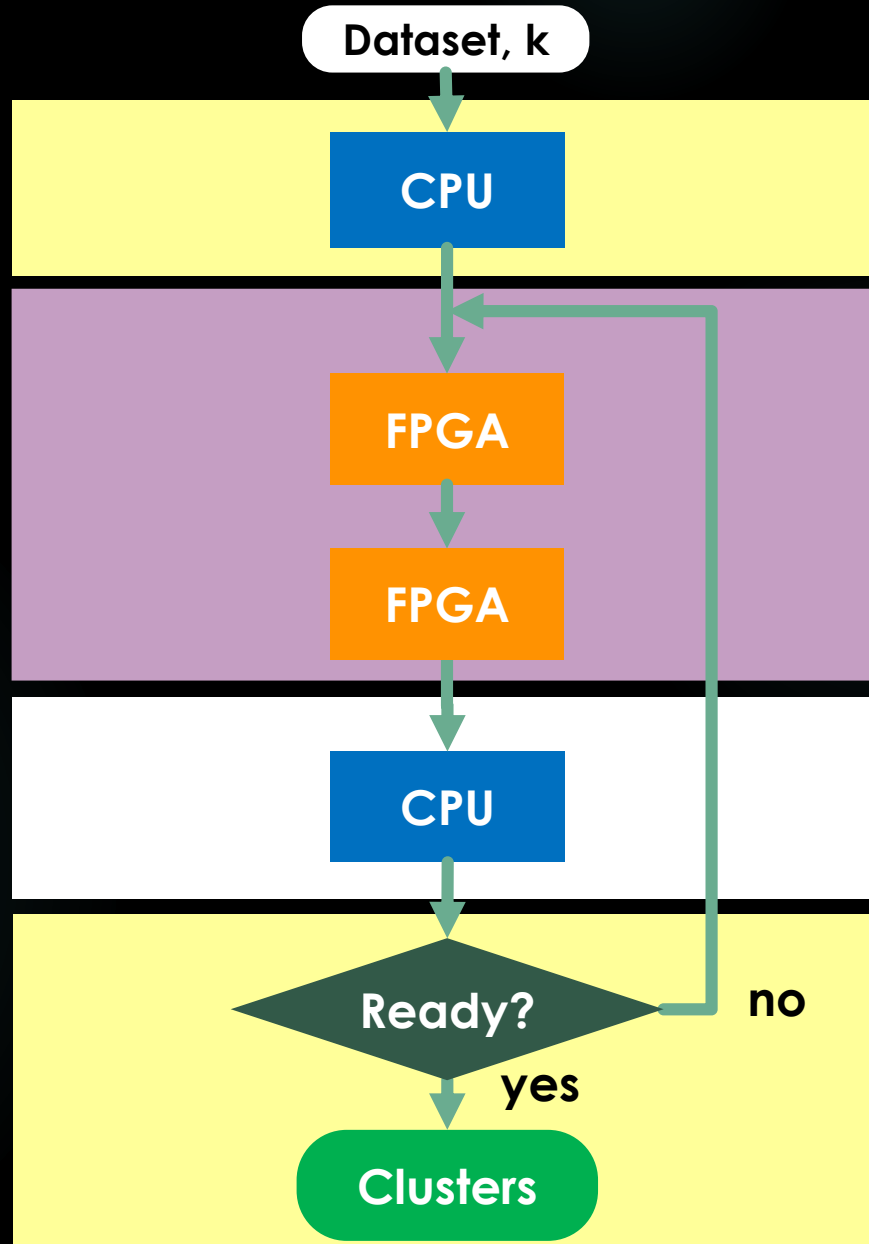
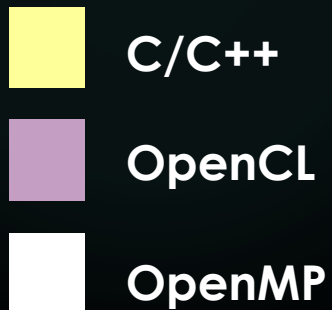
FPGA + CPU + (2x)GPU

# FPGA + CPU

Calculate distances

Get membership of each point

Merge & Update clusters centroids



# FPGA + CPU

SIMD Parallelism  (GPU)	1 A	1 B	1 C	1 D	1 E	4 A	4 B	4 C	4 D	4 E
	2 A	2 B	2 C	2 D	2 E	5 A	5 B	5 C	5 D	5 E
	3 A	3 B	3 C	3 D	3 E	6 A	6 B	6 C	6 D	6 E
Clock Cycle	1	2	3	4	5	6	7	8	9	10
Pipeline Parallelism  (FPGA)	1 A	2 A	3 A	4 A	5 A	6 A				
		1 B	2 B	3 B	4 B	5 B	6 B			
			1 C	2 C	3 C	4 C	5 C	6 C		
				1 D	2 D	3 D	4 D	5 D	6 D	
					1 E	2 E	3 E	4 E	5 E	6 E

Comparison of SIMD Parallelism Versus Pipeline Parallelism  
 OpenCL on FPGAs for GPU Programmers, Intel Altera

<https://www.altera.com/content/dam/altera->

[www/global/en\\_US/pdfs/literature/wp/wp-201406-acceleware-openc1-on-fpgas-for-gpu-programmers.pdf](https://www.altera.com/content/dam/altera-wwww/global/en_US/pdfs/literature/wp/wp-201406-acceleware-openc1-on-fpgas-for-gpu-programmers.pdf)

# FPGA + CPU v0

Function *Kmeans\_Kernel* is

**Input:**

*pts, clusters, npoints, nclusters, ndims;*

**Output:**

*membership;*

*gid*  $\leftarrow$  *get\_global\_id*(0);

**if** *gid* < *npoints* **then**

*index*  $\leftarrow$  0;

*min\_dist*  $\leftarrow$   $\infty$ ;

**for** *c*  $\in$  [0, *nclusters*) **do**

*dist*  $\leftarrow$  0;

**for** *d*  $\in$  [0, *ndims*) **do**

*dist* += (*pts*[*gid* \* *ndims* + *d*] - *clusters*[*c* \* *ndims* + *d*]) \*  
                    (*pts*[*gid* \* *ndims* + *d*] - *clusters*[*c* \* *ndims* + *d*]);

**end**

**if** *dist* < *min\_dist* **then**

*min\_dist*  $\leftarrow$  *dist*;

*index*  $\leftarrow$  *c*;

**end**

*membership*[*gid*]  $\leftarrow$  *index*;

**end**

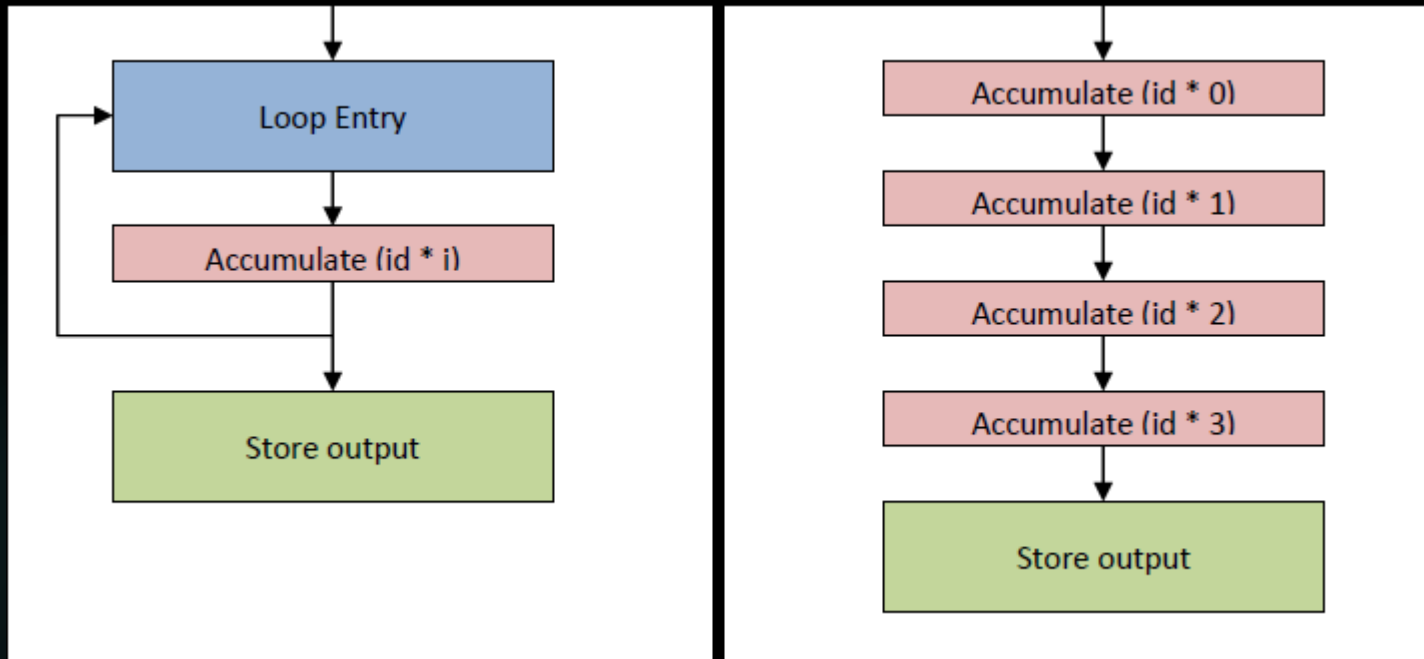
> 200 s/iter

8192p

D=2

K=2

# FPGA + CPU



## Loop Unrolling Example

*OpenCL on FPGAs for GPU Programmers, Intel Altera*

<https://www.altera.com/content/dam/altera->

[www/global/en\\_US/pdfs/literature/wp/wp-201406-acceleware-opencl-on-fpgas-for-gpu-programmers.pdf](https://www.altera.com/content/dam/altera-www/global/en_US/pdfs/literature/wp/wp-201406-acceleware-opencl-on-fpgas-for-gpu-programmers.pdf)

# FPGA + CPU v1

Function *Kmeans\_Kernel* is

**Input:**

*pts, clusters;*

**Output:**

*membership;*

*gid*  $\leftarrow$  *get\_global\_id*(0);

if *gid* < *NPOINTS* then

*index*  $\leftarrow$  0;

*min\_dist*  $\leftarrow$   $\infty$ ;

    for *c*  $\in$  [0, *NCLUSTERS*) do

*dist*  $\leftarrow$  0;

        #pragma unroll;

        for *d*  $\in$  [0, *NDIMS*) do

*dist* += (*pts*[*gid*\**NDIMS*+*d*] - *clusters*[*c*\**NDIMS*+*d*]) \*  
                    (*pts*[*gid*\**NDIMS*+*d*] - *clusters*[*c*\**NDIMS*+*d*]);

        end

        if *dist* < *min\_dist* then

*min\_dist*  $\leftarrow$  *dist*;

*index*  $\leftarrow$  *c*;

    end

*membership*[*gid*]  $\leftarrow$  *index*;

end



# FPGA + CPU v2

Function *Kmeans\_Kernel* is

**Input:**

*pts, clusters;*

**Output:**

*membership;*

```
gid ← get_global_id(0);  
if gid < NPOINTS then  
    index ← 0;  
    min_dist ← ∞;  
    for c ∈ [0, NCLUSTERS) do  
        dist ← 0;  
        #pragma unroll;  
        for d ∈ [0, NDIMS) do  
            dist += (pts[d*NPOINTS+gid] - clusters[c*NDIMS+d]) *  
                (pts[d*NPOINTS+gid] - clusters[c*NDIMS+d]);  
        end  
        if dist < min_dist then  
            min_dist ← dist;  
            index ← c;  
        end  
    end  
    membership[gid] ← index;  
end
```

# FPGA + CPU v3

Function *Kmeans\_Kernel* (Workgroup size = *NCLUSTERS\*NDIMS*) is

**Input:**

*pts, clusters;*

**Output:**

*membership;*

*gid*  $\leftarrow$  *get\_global\_id*(0);

*lid*  $\leftarrow$  *get\_local\_id*(0);

*clusters\_local*[*NCLUSTERS\*NDIMS*];

*clusters\_local*[*lid*]  $\leftarrow$  *clusters*[*lid*];

*barrier*(CLK\_LOCAL\_MEM\_FENCE);

*index*  $\leftarrow$  0;

*min\_dist*  $\leftarrow$   $\infty$ ;

**for** *c*  $\in$  [0, *NCLUSTERS*) **do**

*dist*  $\leftarrow$  0;

**#pragma unroll**

**for** *d*  $\in$  [0, *NDIMS*) **do**

*dist* +=

        (*pts*[*d\*NPOINTS*+*gid*] - *clusters\_local*[*c\*NDIMS*+*d*]) \*

        (*pts*[*d\*NPOINTS*+*gid*] - *clusters\_local*[*c\*NDIMS*+*d*]);

**end**

**if** *dist* < *min\_dist* **then**

*min\_dist*  $\leftarrow$  *dist*;

*index*  $\leftarrow$  *c*;

**end**

*membership*[*gid*]  $\leftarrow$  *index*;

**end**

# FPGA + CPU v4

0.34 s/iter  
8192p  
D=2  
K=2

Function *Kmeans\_Kernel* (Workgroup size =  $NCLUSTERS * NDIMS$ ) is

**Input:**

*feature, clusters;*

**Output:**

*distances;*

*gid*  $\leftarrow$  *get\_global\_id*(0);

*lid*  $\leftarrow$  *get\_local\_id*(0);

*clusters\_local*[ $NCLUSTERS * NDIMS$ ];

*clusters\_local*[*lid*]  $\leftarrow$  *clusters*[*lid*];

*barrier*(CLK\_LOCAL\_MEM\_FENCE);

*index*  $\leftarrow$  0;

*min\_dist*  $\leftarrow$   $\infty$ ;

**#pragma unroll 4**

**for** *c*  $\in$  [0,  $NCLUSTERS$ ) **do**

*dist*  $\leftarrow$  0;

**#pragma unroll**

**for** *d*  $\in$  [0,  $NDIMS$ ) **do**

*diff* =

*feature*[ $d * NPOINTS + gid$ ] - *clusters\_local*[ $c * NDIMS + d$ ];

*dist* += *pown*(*diff*, 2);

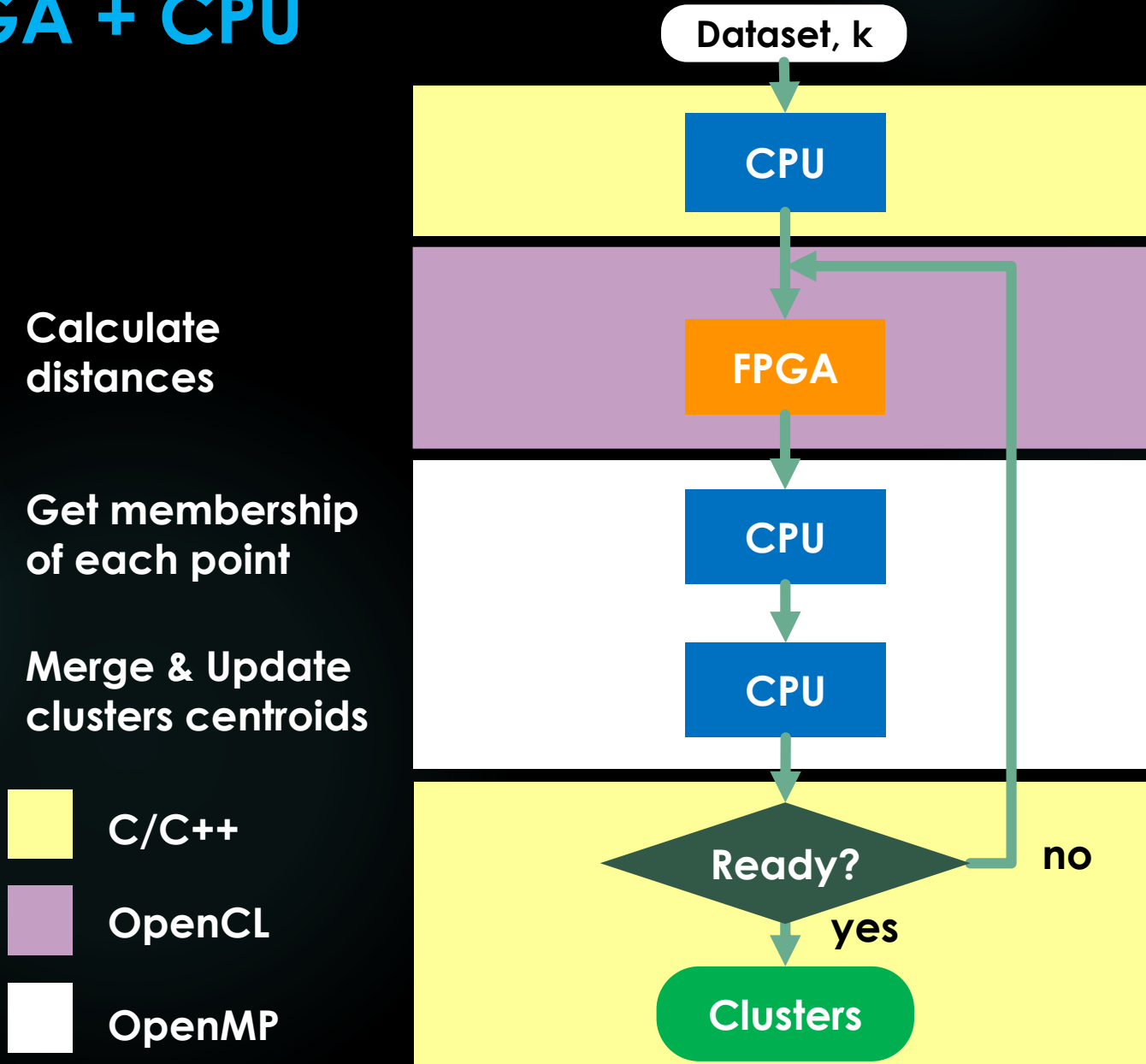
**end**

*distances*[ $gid * NCLUSTERS + c$ ]  $\leftarrow$  *dist*;

**end**

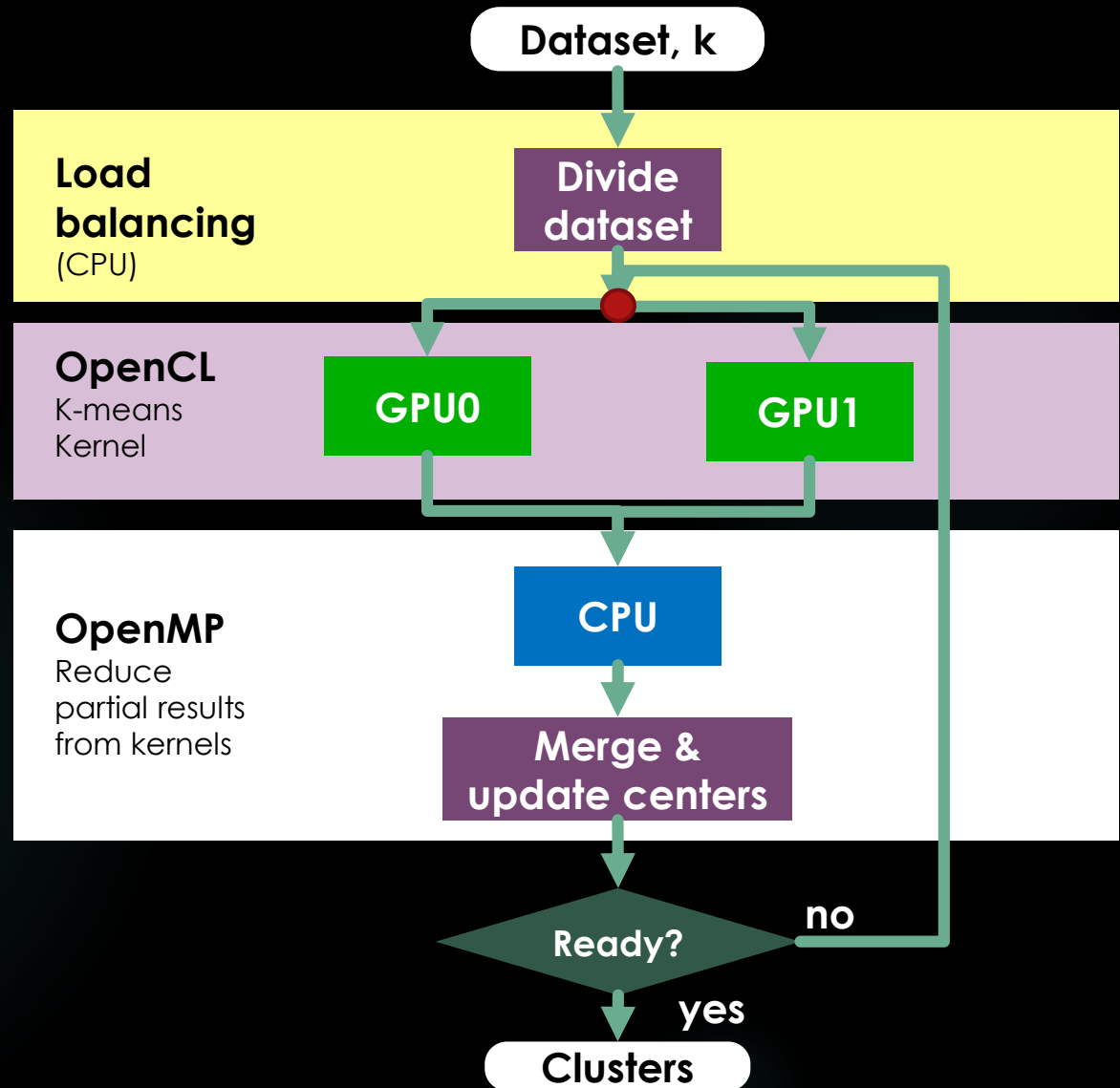
**end**

# FPGA + CPU



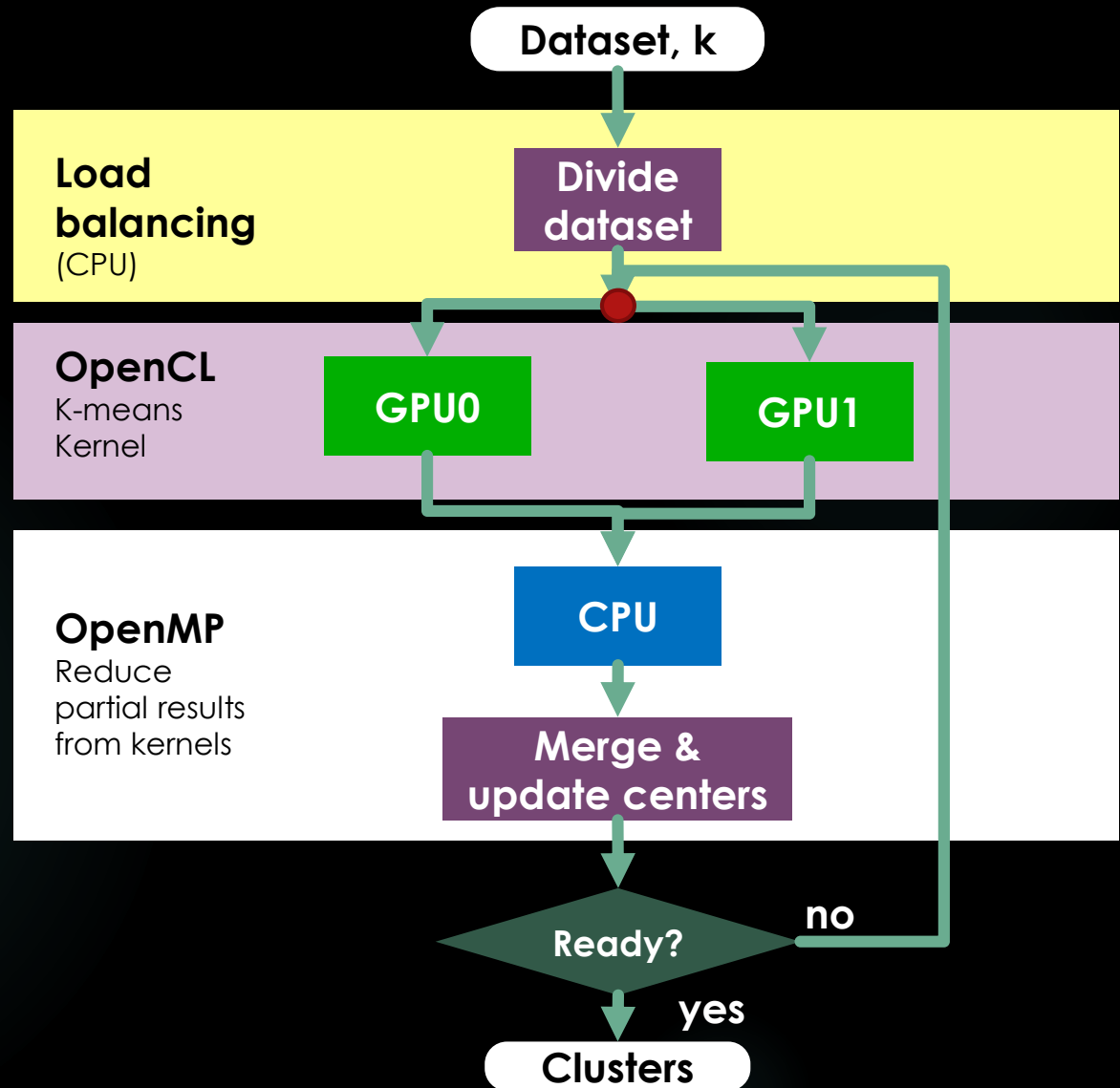
# (2x)GPU + CPU

- ▶ No need to adapt the kernel
- ▶ Focus on orchestrating both devices



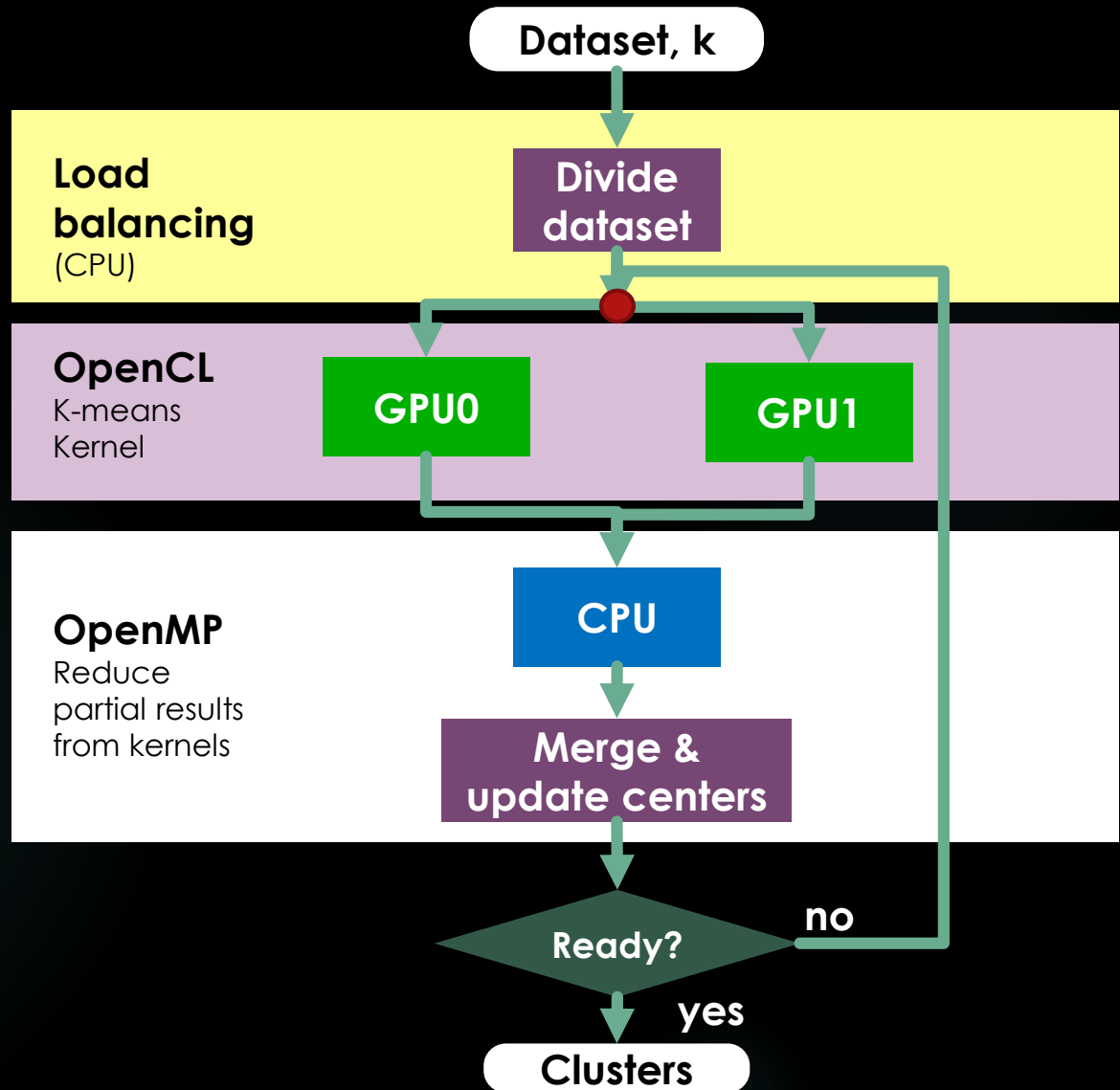
# (2x)GPU + CPU

- ▶ OpenCL buffer sharing causes performance degradation



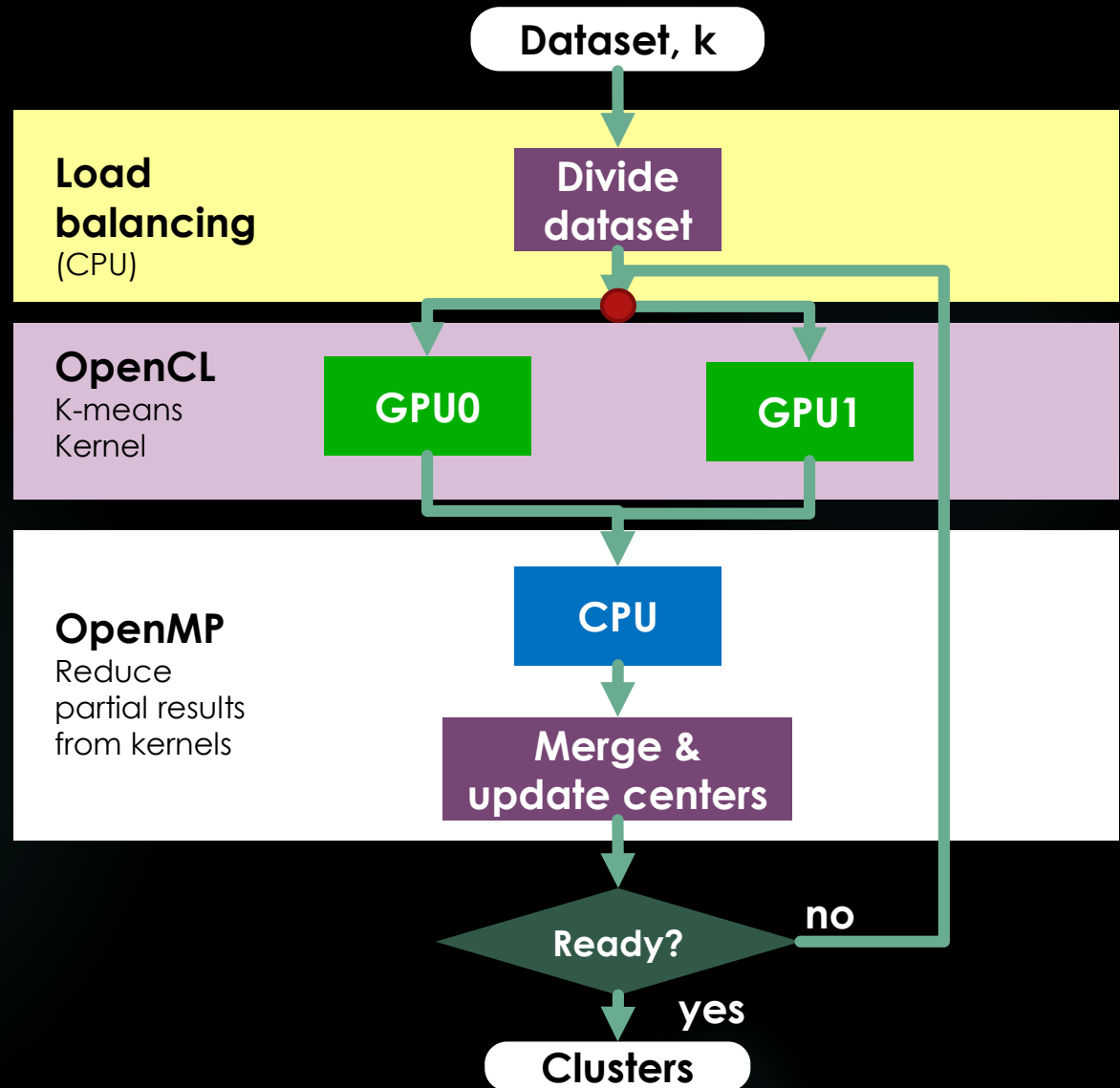
# (2x)GPU + CPU

- ▶ To preserve coalescing, input points must be stored as a SoA
  - ▶ Buffers must be swapped



# (2x)GPU + CPU

- ▶ Both devices are identical, so the load can be evenly distributed





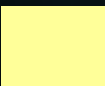


# FPGA + CPU + (2x)GPU

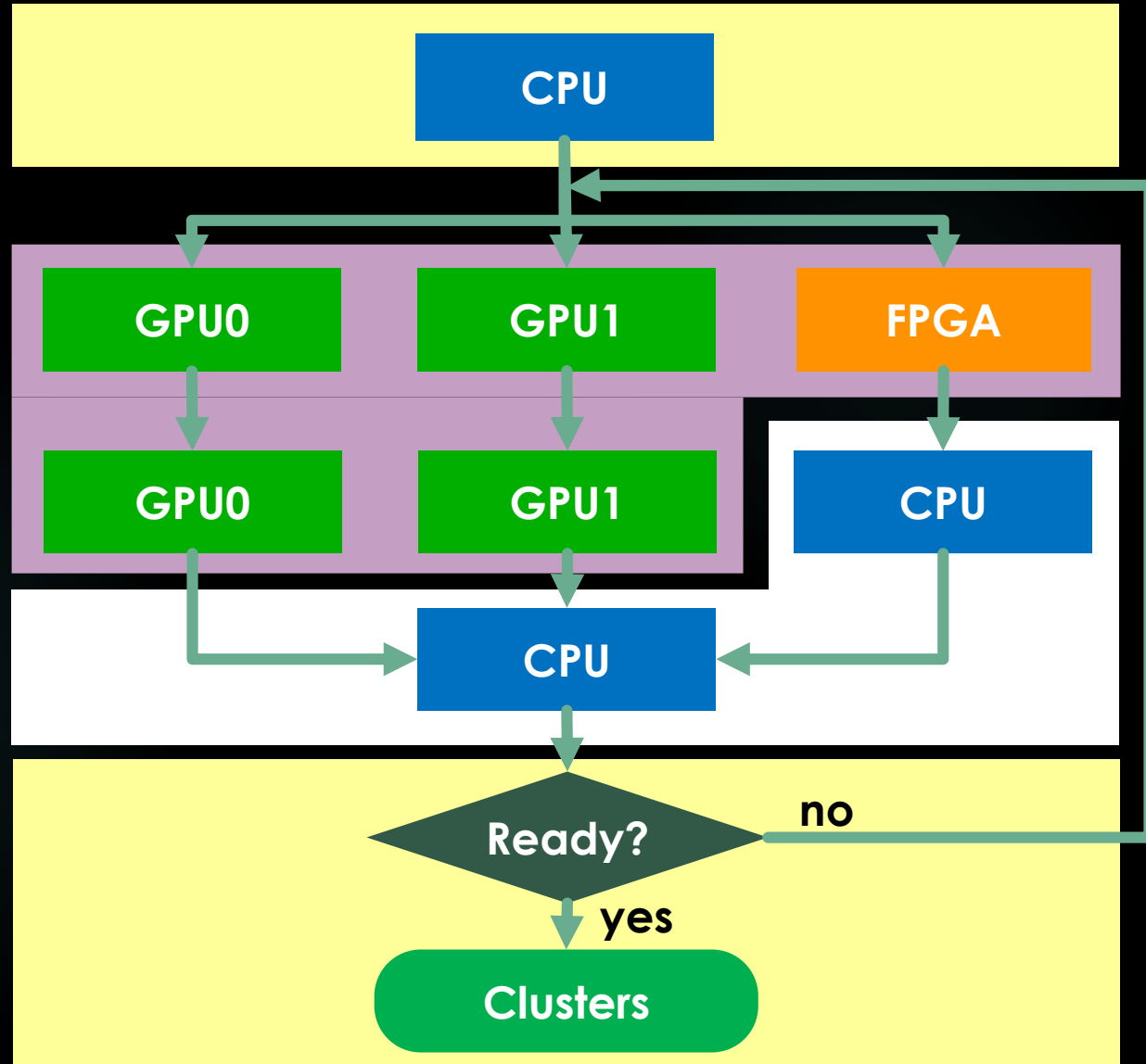
Split work for all devices

Calculate distances

Get membership of each point

Merge & Update clusters centroids

-  C/C++
-  OpenCL
-  OpenMP





# 4. Overall results

Methodology

Test results

# Methodology

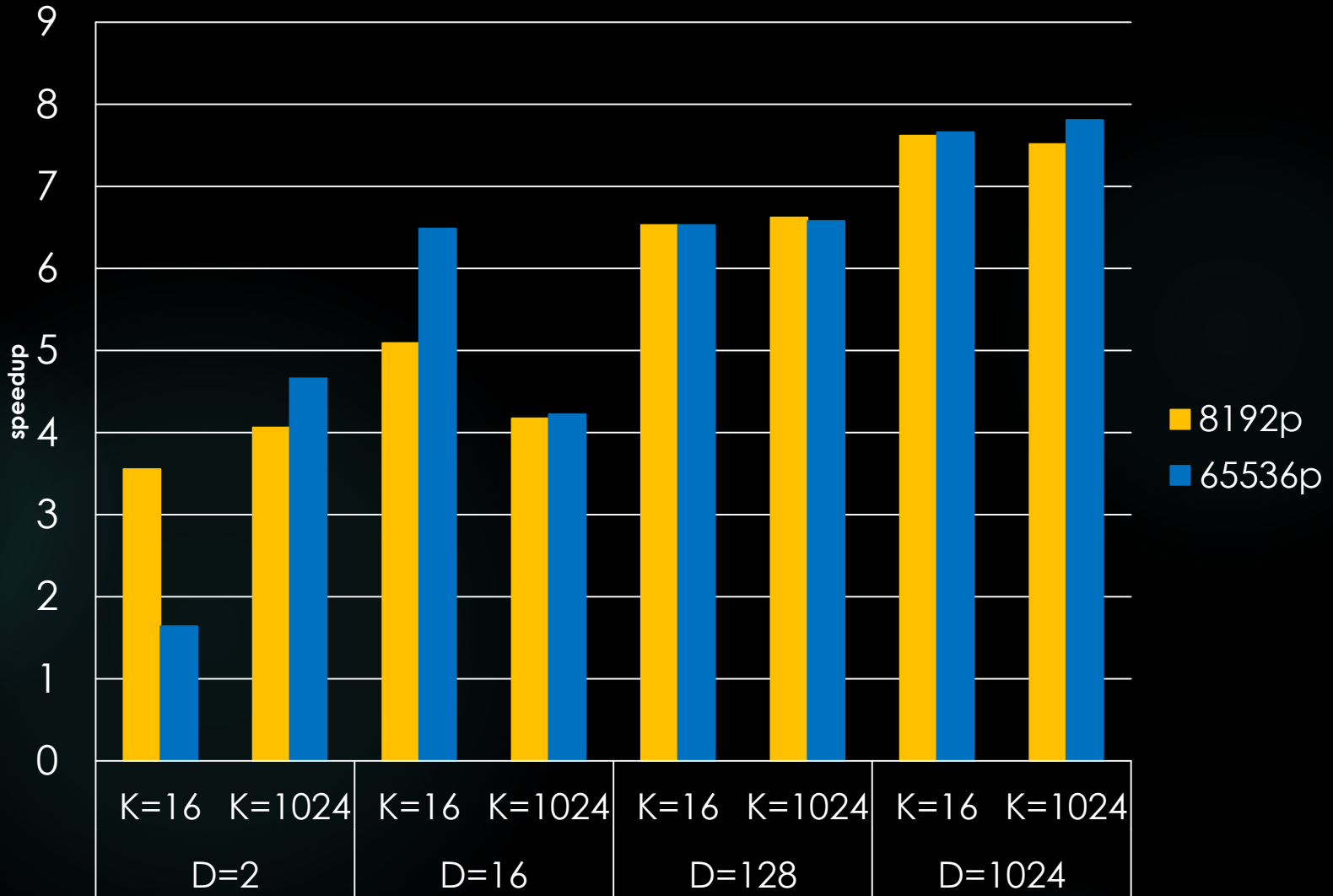
## Compare execution time:

- ▶ **Base system: Sequential**
- ▶ **OpenMP (8 threads)**
- ▶ **1 GPU**
- ▶ **2 GPUs**
- ▶ **FPGA**
- ▶ **CPU-(2x)GPU-FPGA**

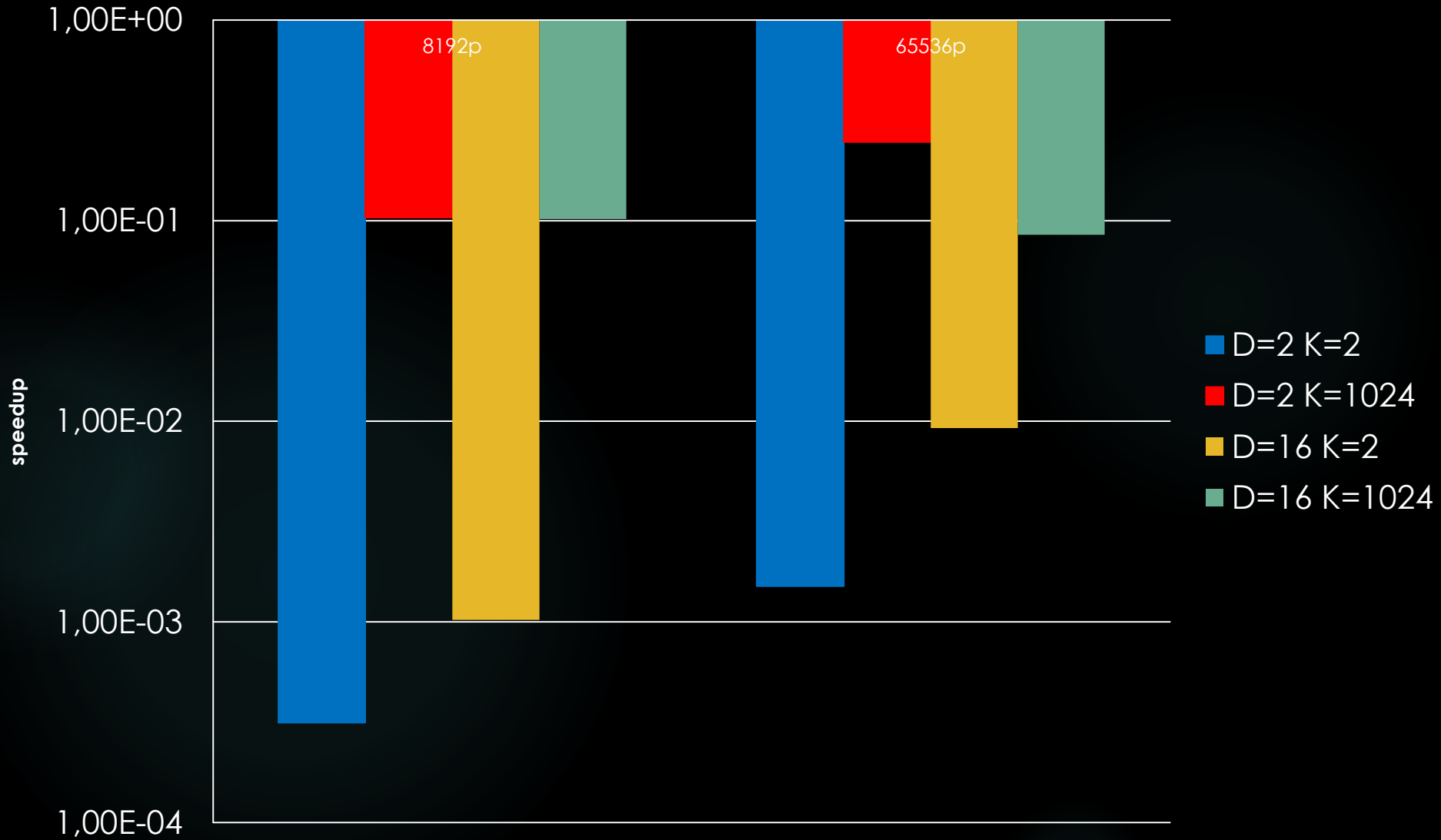
## Datasets used:

- ▶ **8192 points**
  - ▶ 2 dimensions
  - ▶ 16 dimensions
  - ▶ 128 dimensions
  - ▶ 1024 dimensions
- ▶ **65536 points**
  - ▶ 2 dimensions
  - ▶ 16 dimensions
  - ▶ 128 dimensions
  - ▶ 1024 dimensions
- ▶ **4194304 points**
  - ▶ 2 dimensions
  - ▶ 16 dimensions
  - ▶ 128 dimensions
  - ▶ 1024 dimensions

# OpenMP



# FPGA + CPU

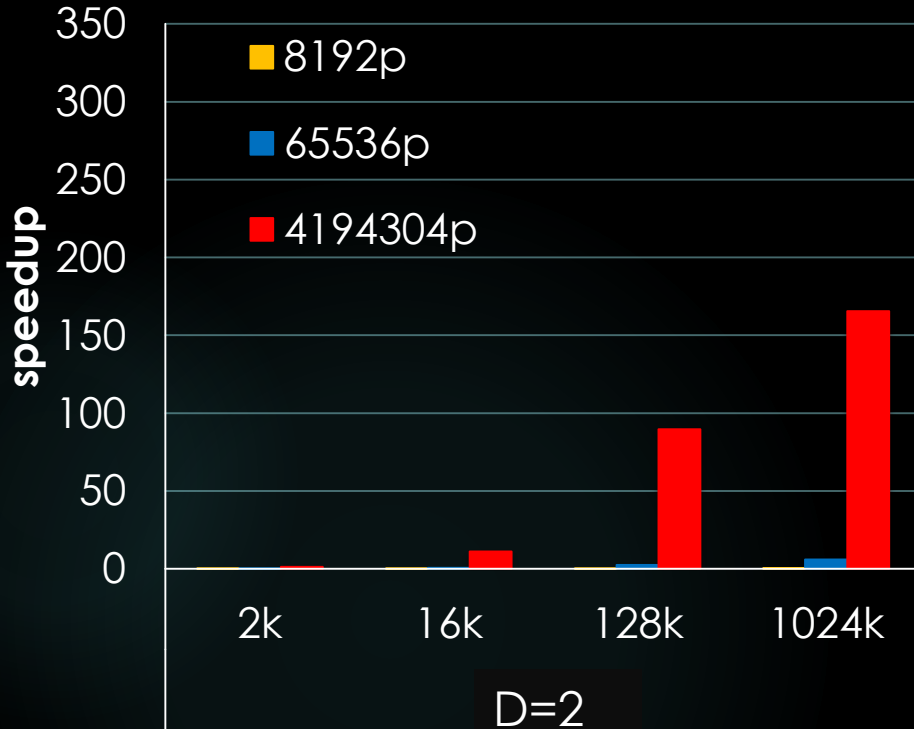


# (2x)GPU + CPU



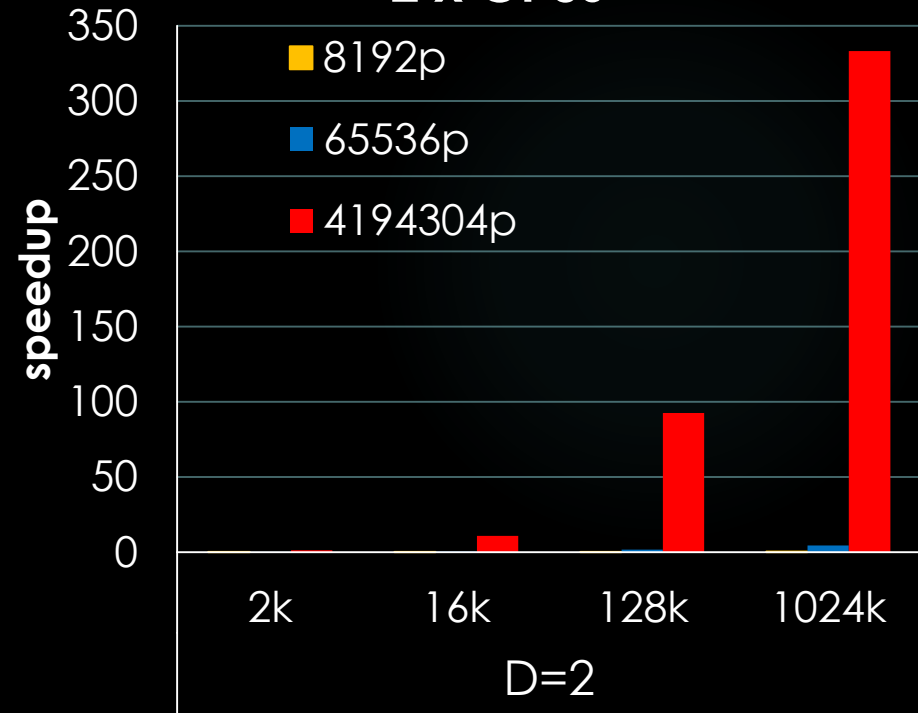
164 x  
speedup

1 GPU



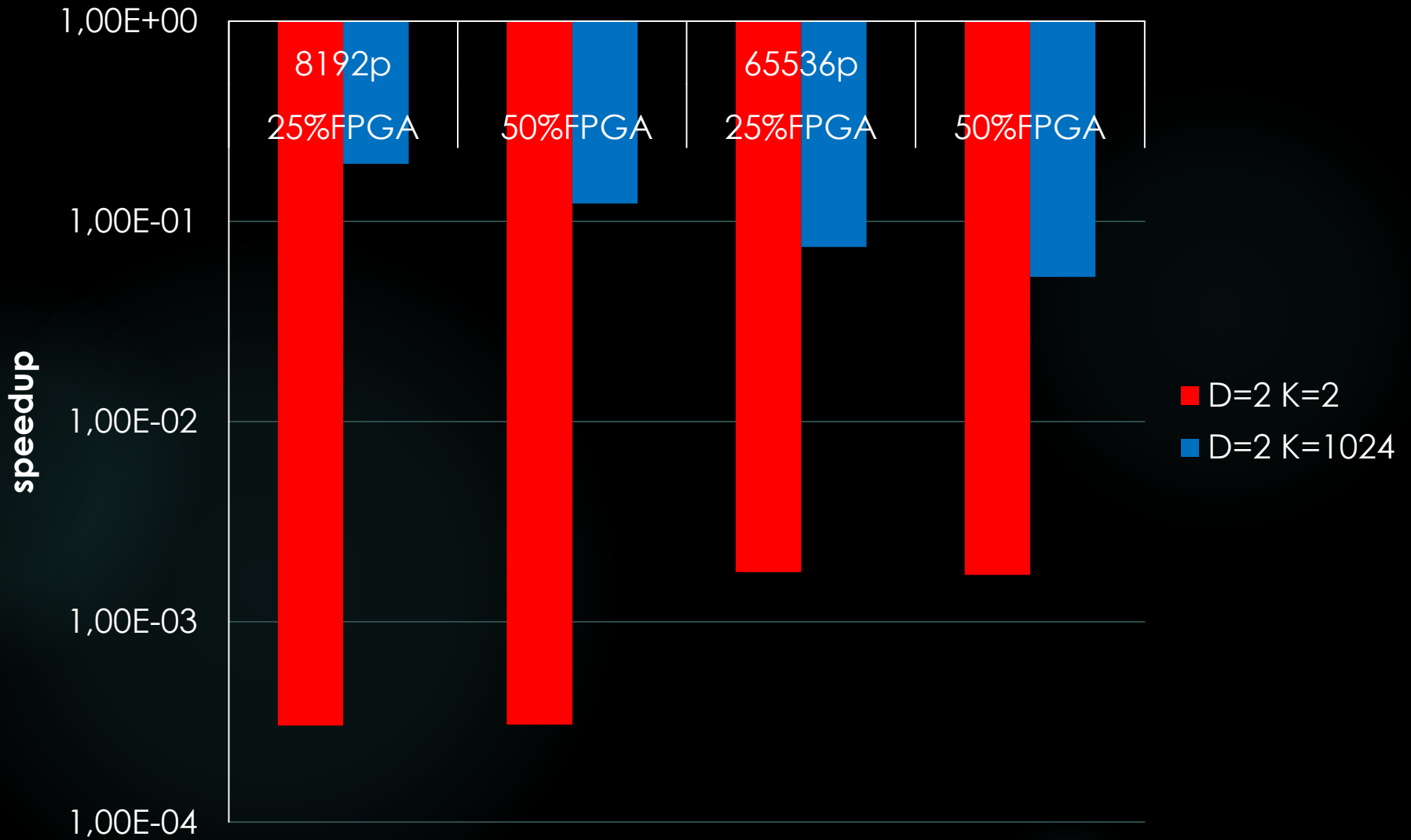
328 x  
speedup

2 x GPUs

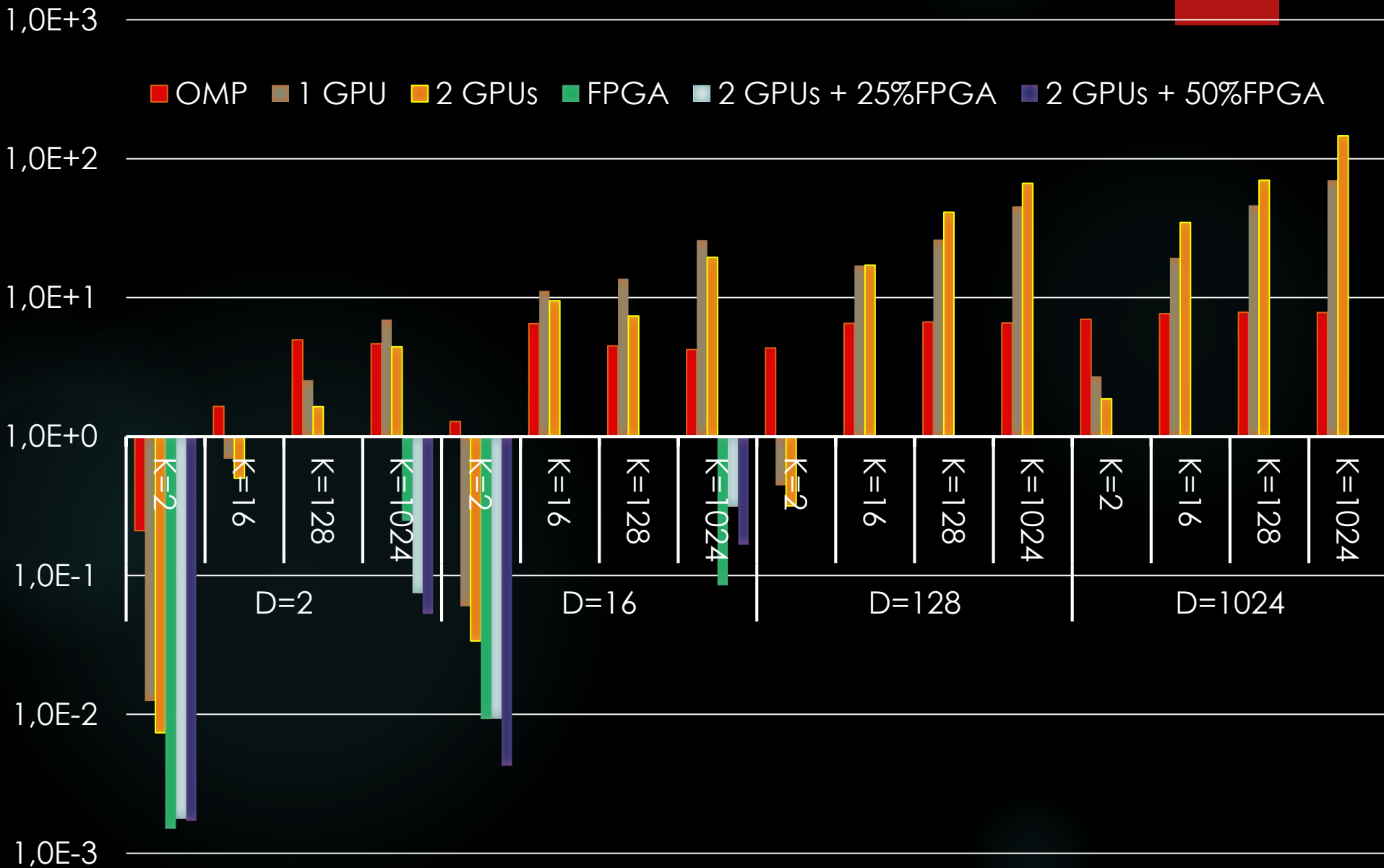


- ▶ The 2 GPU implementation requires large problem sizes for the distribution to be worthy

# FPGA + CPU + (2x)GPU

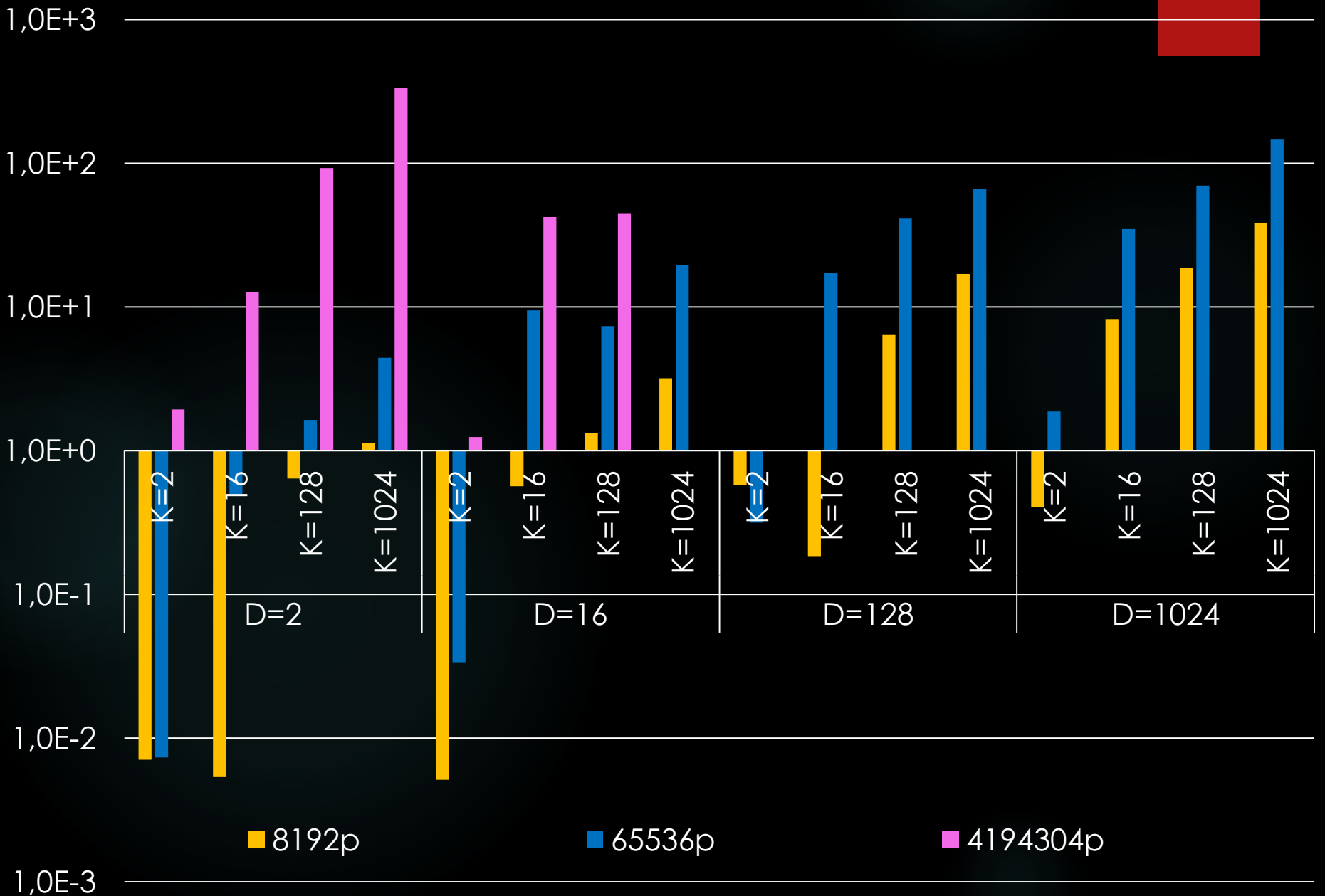


# Speedup comparison Npoints = 65536





# Npoints 2-GPUS Speedup Comparison



# 5. Conclusions

# Conclusions

- ▶ Small datasets => **OMP** is the best choice (delegating on other devices is not worth it – high I/O time).
- ▶ Large datasets => **GPUs** (massive parallelism). **328 x speedup!** 😊
- ▶ Difficult to get advantage of **FPGA's** resources by pipelining the k-means algorithm.
- ▶ **Integrated GPU & FPGA** version to further analyze the tradeoff between the overall execution time and the power usage.
- ▶ **Dynamic load balancer** - split the workload depending on specific criteria (e.g. execution time of previous iterations for each device).

$$O(\#iterations \times N \times D \times K)$$

# References

1. Tang, Q. Y., & Khalid, M. A. (2016). Acceleration of K-Means Algorithm Using Altera SDK for OpenCL. ACM Transactions on Reconfigurable Technology and Systems (TRETs), 10(1), 6.
2. K-Means. Rodinia. Retrieved April 23, 2017, from [www.cs.virginia.edu/~skadron/wiki/rodinia/index.php/K-Means](http://www.cs.virginia.edu/~skadron/wiki/rodinia/index.php/K-Means)
3. OpenMP. Retrieved April 23, 2017, from [www.openmp.org/](http://www.openmp.org/)
4. Khronos Group. OpenCL - The open standard for parallel programming of heterogeneous systems. Retrieved April 23, 2017, from [www.khronos.org/opencl/](http://www.khronos.org/opencl/)
5. Intel. Intel FPGA SDK for OpenCL. Retrieved April 23, 2017, from [www.altera.com/en\\_US/pdfs/literature/hb/opencl-sdk/aocl-best-practices-guide.pdf](http://www.altera.com/en_US/pdfs/literature/hb/opencl-sdk/aocl-best-practices-guide.pdf)

# Source Code



▶ [https://github.com/  
MarcosCM/Heterogeniuses](https://github.com/MarcosCM/Heterogeniuses)