



UNIVERSITÀ
DI TRENTO

A Parallel approach to K-Means with OMP and MPI

Introduction to Parallel Computing

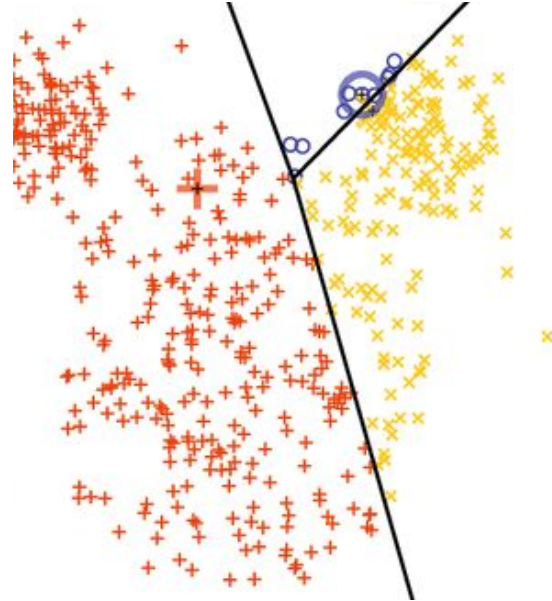


Authors: Elia Zonta, Alex Pegoraro

What is K-Means

A geometric clustering [1] algorithm with applications such as:

- Data analysis
- Pattern recognition
- Image segmentation
- ...



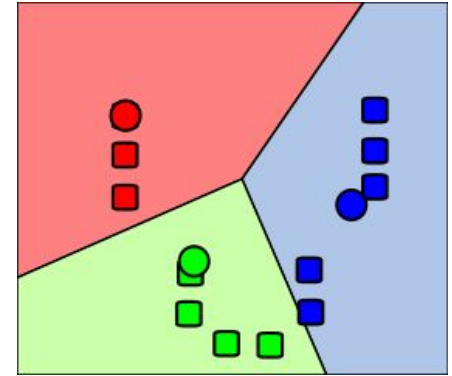
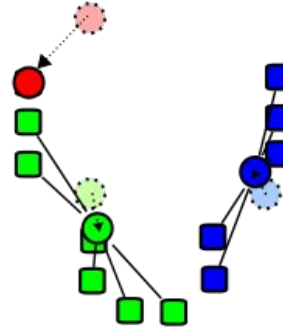
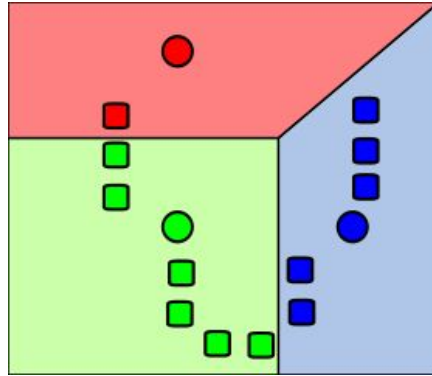
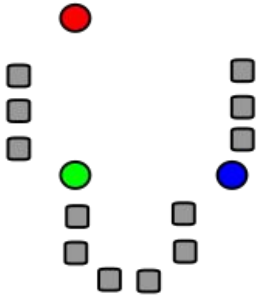
Objective

Our goal is to apply different parallelization techniques to K-Means, studying the effects, benefits and drawbacks.

Every experiments has been done on the UniTN-HPC cluster



The Algorithm [1]



Authors: Elia Zonta, Alex Pegoraro

The Algorithm [2]

```
random_init_centroids(points, centroids)
```

```
for e in epochs:
```

```
    assign_points_to_cluster(points, clusters)
```

```
    cumulative = sum_points_in_cluster(clusters)
```

```
    compute_centroids(cumulative)
```

```
    if delta < tolerance:
```

```
        break // convergence reached
```



The Dataset

- Synthetic data generator script
- Uniform distribution
- Arbitrary number of features
- Arbitrary number of entries
- Arbitrary upper and lower bounds
- Both data points and initial centroids generated with it, to ensure fairness

```
std::uniform_real_distribution<double> uniform();
```



Authors: Elia Zonta, Alex Pegoraro

The Parallel Approach (OpenMP)

```
random_init_centroids(points, centroids)
```

```
for e in epochs:
```

```
    #pragma omp parallel for schedule(static, static_cast<int>(...)) reduction(+:delta)
```

```
    assign_points_to_cluster(points, clusters)
```

```
    #pragma omp parallel for schedule(static, static_cast<int>(...)) reduction(+:delta)
```

```
    cumulative = sum_points_in_cluster(clusters)
```

```
    #pragma omp parallel for schedule(static, n_features)
```

```
    compute_centroids(cumulative)
```

```
    if delta < tolerance:
```

```
        break // convergence reached
```



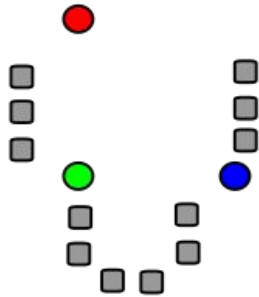
The Parallel Approach (MPI) [1]

```
random_init_centroids(points, centroids)
if (Master) MPI_Send(points) else MPI_Recv(points)
MPI_Bcast(centroids)

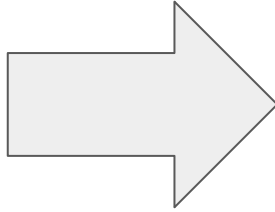
for e in epochs:
    assign_poits_to_cluster(points, clusters)
    cumulative = sum_points_in_cluster(clusters)
    MPI_Allreduce(cumulative)
    compute_centroids(cumulative)
    if delta < tolerance:
        break // convergence reached
```



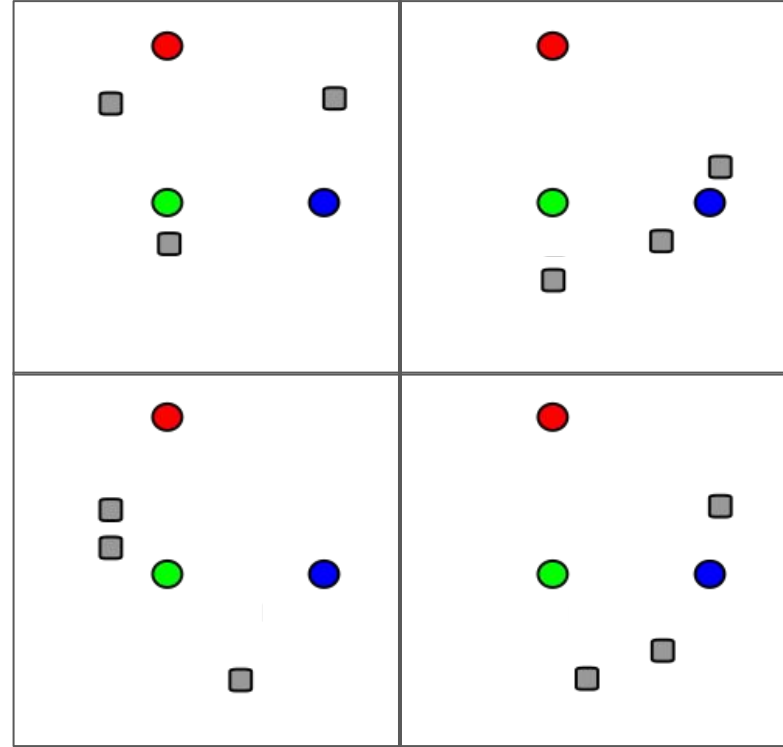
The Parallel Approach (MPI) [2]



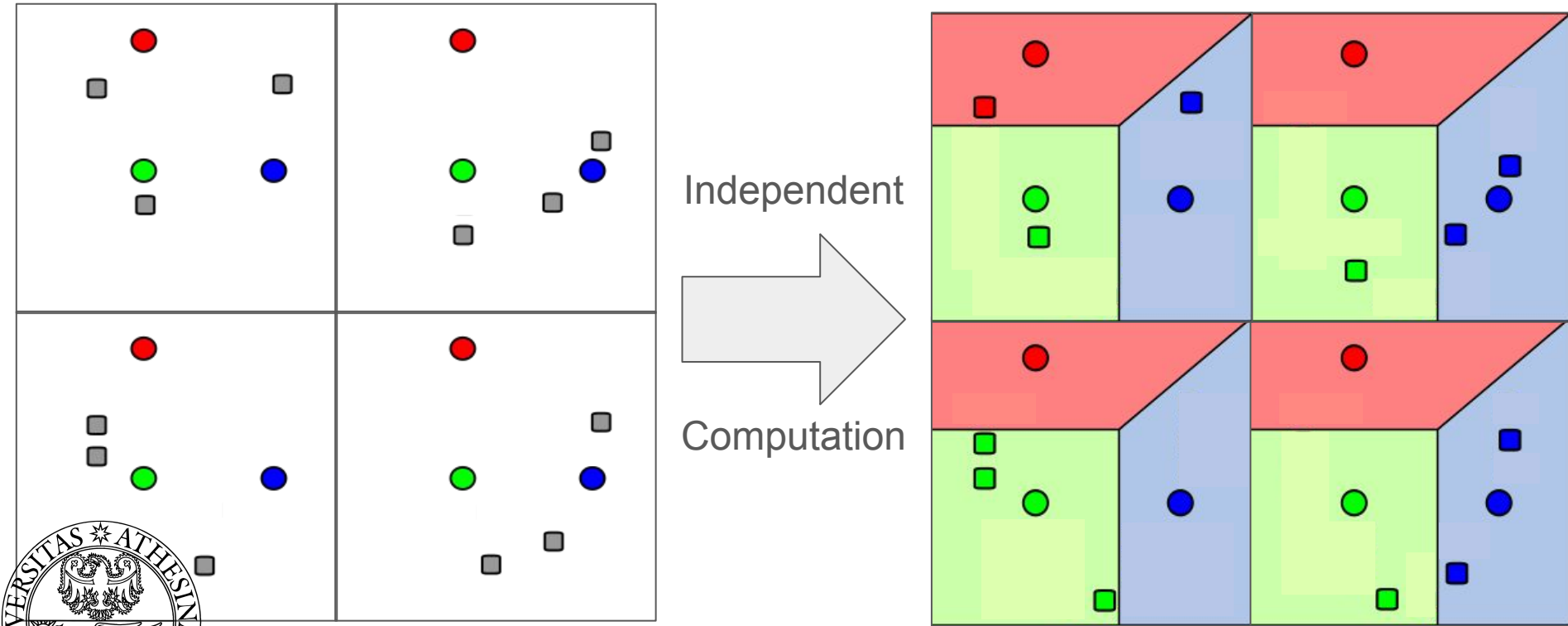
MPI_Send(Points)



MPI_Bcast(Centroids)

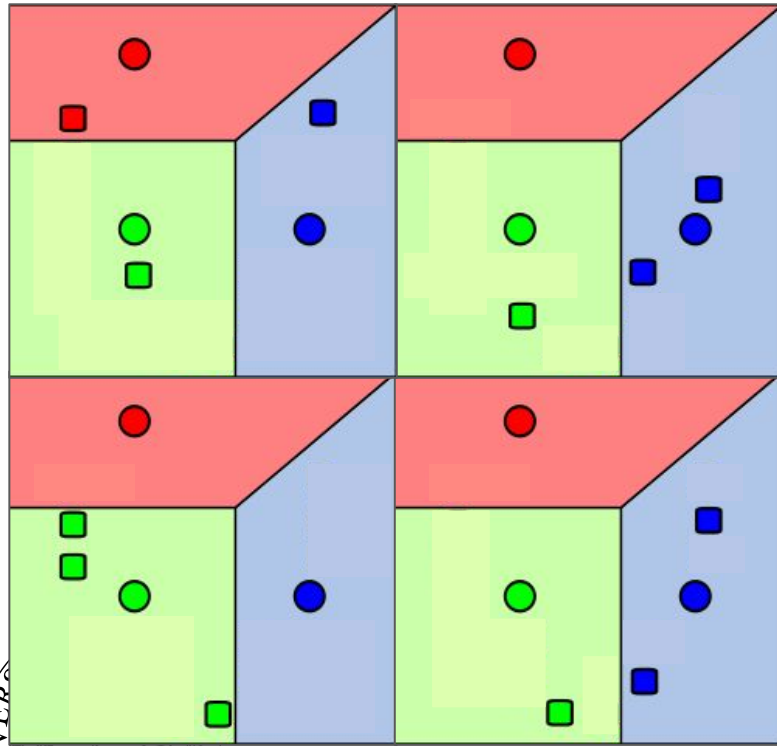


The Parallel Approach (MPI) [3]

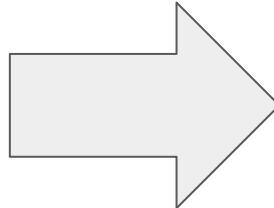


Authors: Elia Zonta, Alex Pegoraro

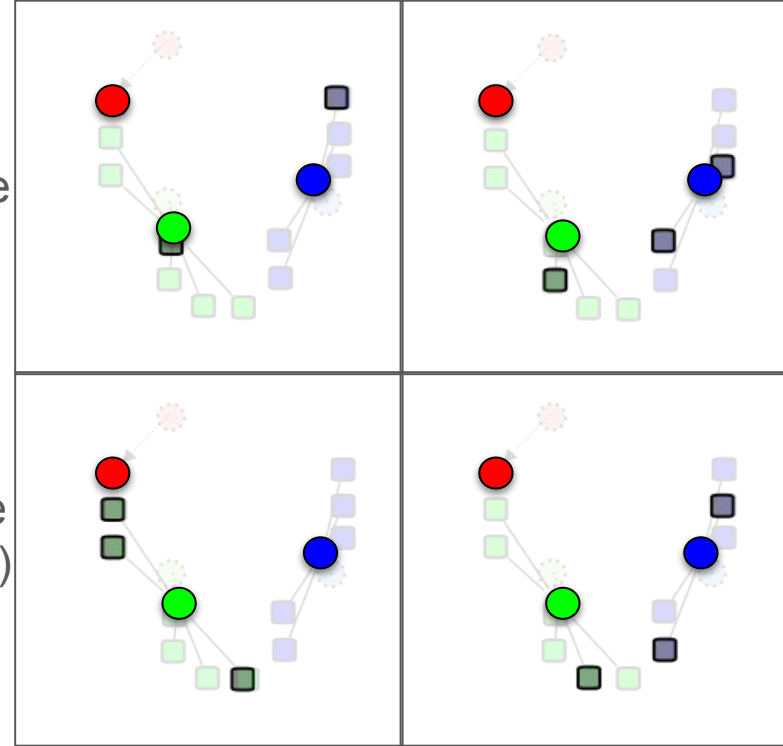
The Parallel Approach (MPI) [4]



MPI_Allreduce
(cumulative)



MPI_Allreduce
(point_counter)



Authors: Elia Zonta, Alex Pegoraro



Correctness

Base file: out/serial_out.csv

n_points: 65536, n_clusters: 64, n_dimensions: 8, tolerance: 0.001

Comparison with files in: out

mpi_asynch_strong_out_1.csv: points OK, centroids OK

mpi_asynch_strong_out_128.csv: points OK, centroids OK

mpi_asynch_strong_out_16.csv: points OK, centroids OK

mpi_asynch_strong_out_2.csv: points OK, centroids OK

mpi_asynch_strong_out_256.csv: points OK, centroids OK

mpi_asynch_strong_out_32.csv: points OK, centroids OK

mpi_asynch_strong_out_4.csv: points OK, centroids OK

mpi_asynch_strong_out_64.csv: points OK, centroids OK

mpi_asynch_strong_out_8.csv: points OK, centroids OK

mpi_asynch_weak_out_1.csv: LESS points

mpi_asynch_weak_out_128.csv: MORE points, 64509 DIFFERENT points, 64 DIFFERENT centroids

mpi_asynch_weak_out_16.csv: LESS points

mpi_asynch_weak_out_2.csv: LESS points

mpi_asynch_weak_out_256.csv: MORE points, 64510 DIFFERENT points, 64 DIFFERENT centroids

mpi_asynch_weak_out_32.csv: LESS points

mpi_asynch_weak_out_4.csv: LESS points

mpi_asynch_weak_out_64.csv: 64543 DIFFERENT points, 64 DIFFERENT centroids



Authors: Elia Zonta, Alex Pegoraro

Computing System

UniTrento@HPC Cluster:

- 142 CPU nodes for a total of 7.674 cores
- 10 GPU nodes for a total of 48.128 CUDA cores
- 2 frontend nodes
- 65 TB of Ram
- Total theoretical peak performance: 478,1 TFLOPs
- Theoretical peak performance CPU: 422,7 TFLOPs
- Theoretical peak performance GPU: 55,4 TFLOPs
- 10Gb/s network
- Both nodes with Infiniband and Omni-Path connectivity.
- Linux CentOS 7 and PBS as the cluster workload manager.



Authors: Elia Zonta, Alex Pegoraro

Benchmark

For strong scaling and serial algorithm:

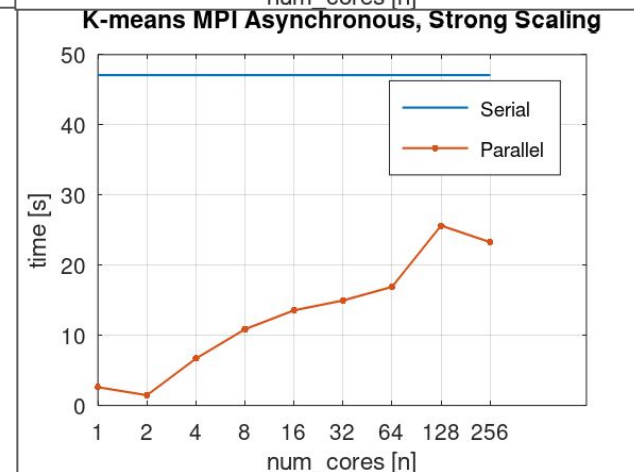
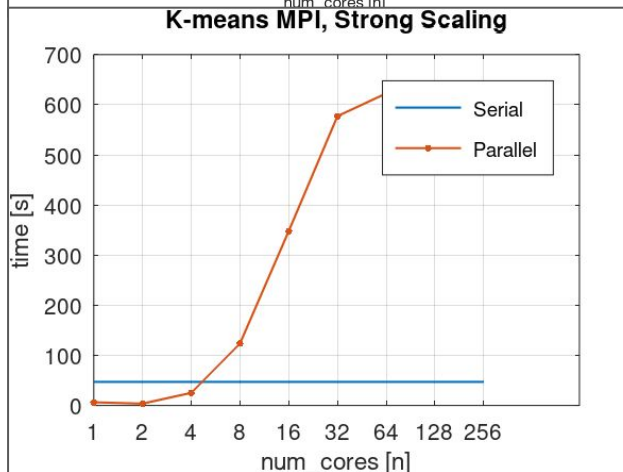
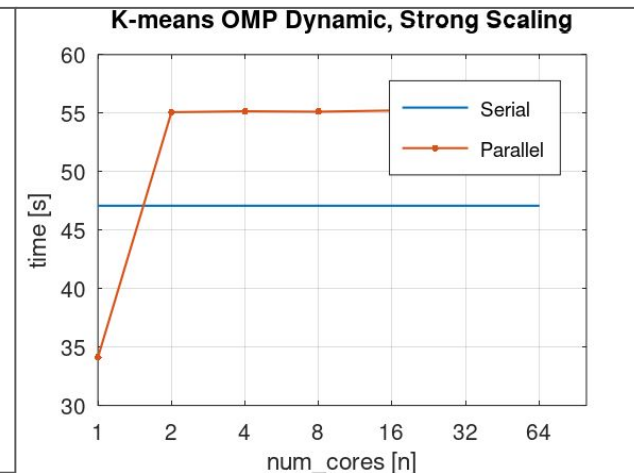
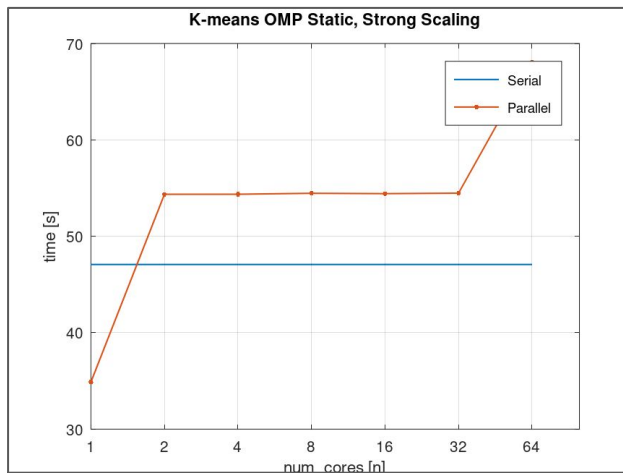
- 65536 data points
- 64 centroids
- 8-dimensional feature space
- 128 epochs
- up to 64 OMP threads
- up to 256 MPI processors

For weak scaling:

- baseline of 1024 data points, increased accordingly to core size
- other parameters identical to strong scaling

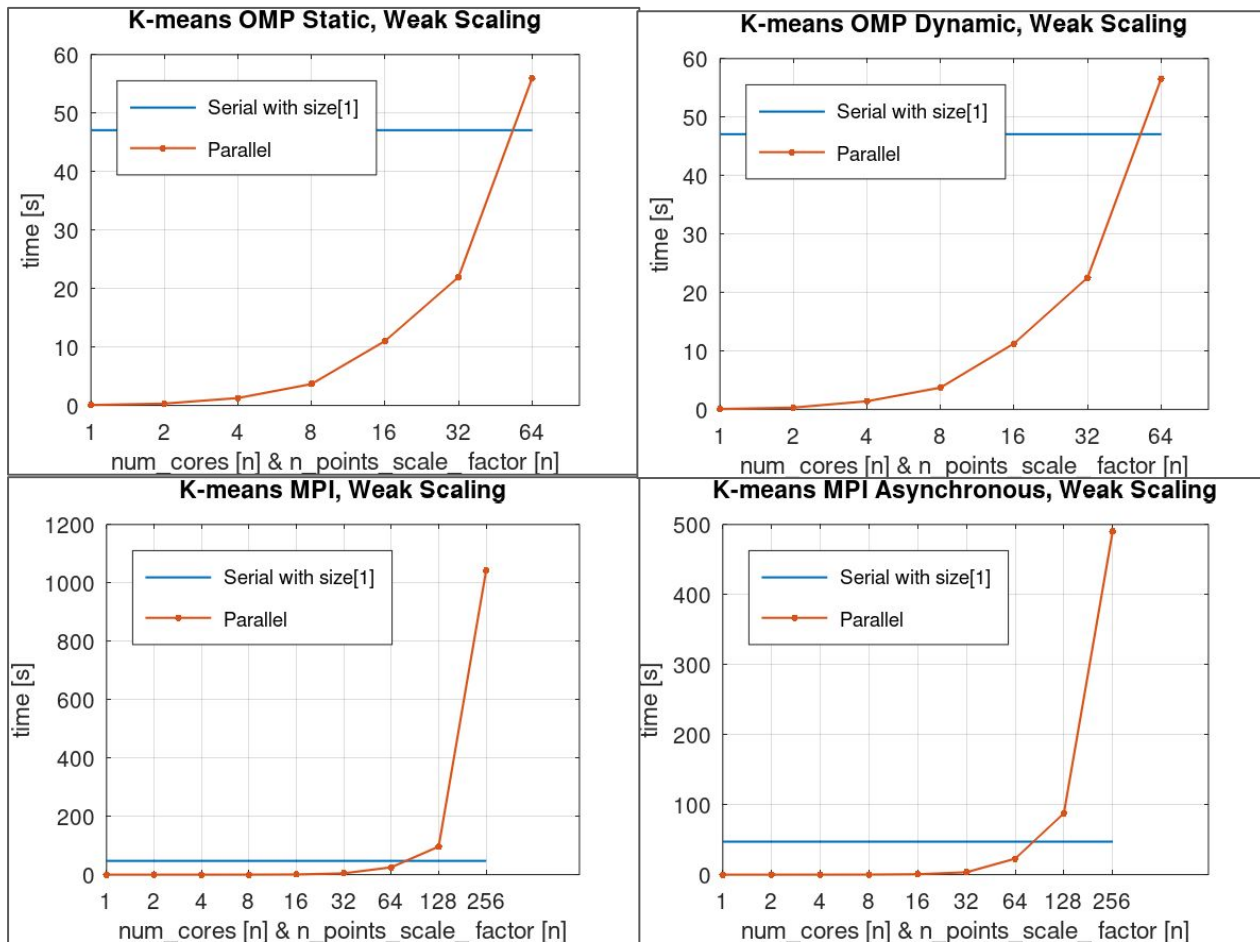


Results[1]



Authors: Elia Zonta, Alex Pegoraro

Results[2]



Authors: Elia Zonta, Alex Pegoraro



Conclusion

The main bottleneck of K-Means parallelization is represented by the **initial messages** required to **distribute points**.



Pictures and References

Slide 1:[1] <https://theory.stanford.edu/~sergei/papers/kMeans-socg.pdf>

Slide 2:

https://commons.wikimedia.org/wiki/File:K-means_convergence.gif

Slide 4:

https://commons.wikimedia.org/wiki/File:K_Means_Example_Step_1.svg

https://commons.wikimedia.org/wiki/File:K_Means_Example_Step_2.svg

https://commons.wikimedia.org/wiki/File:K_Means_Example_Step_3.svg

https://commons.wikimedia.org/wiki/File:K_Means_Example_Step_4.svg

Slides 9,10,11: Same four pictures of slide 4, but crafted.





UNIVERSITÀ
DI TRENTO

Thanks for the attention !

A Parallel approach to K-Means with OMP and MPI

Introduction to Parallel Computing



Authors: Elia Zonta, Alex Pegoraro