Parallel Programming - Middle term assignment
2D K-Means (OpenMP Version)

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Abstract

In this work, I will study the 2D k-Means algorithm. I will compare the sequential version of the program with the parallel version. I will describe the code I've used and the obtained speed up.

1 Introduction

The assignment consists in the study of the parallel version of K-Means. Starting from k random true centroids [in the 2D square with diagonal $(0,0),(1,1)$], the algorithm generates N random points with deviation σ.

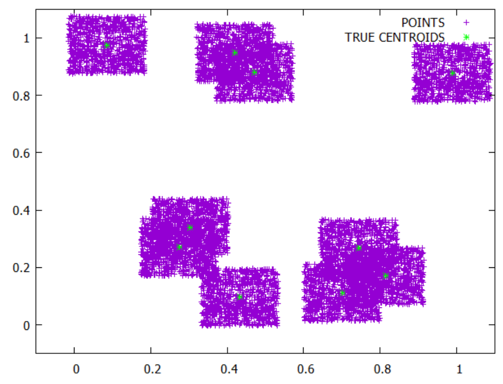


Figure 1: Points visualization

The goal is to find true centroids, starting from k random points of the dataset.

2 Data structure

Generic points and centroids are organized in structures of arrays.

```
typedef struct {
    double x[N];
    double y[N];
} PointsVec;


typedef struct {
    double x[k];
    double y[k];
    int n_points[k];
} CentroidsVec;
```

x and y are the arrays of the Cartesian coordinates; *n_points* is the array in which the algorithm saves the number of points that belong to a centroid.

3 The algorithms

In this report, two K-means algorithms will be studied: the main difference is the way in which the work is divided among all the threads. Both the algorithms are written in OpenMP: in the first one (FV) the points structure is divided in L blocks (L = active threads) and each block is manually assigned to a specific thread. In order to do that, one thread (the master) generates tasks for all the other threads.
In the second one (SV) the compiler chooses how to divide the work ('pragma omp parallel for' directive).

Algorithm 1 K-means FV(points, centroids, n_thr)

```
# pragma omp parallel num_threads(n_thr)
# pragma omp master
    centroidsVec master_centr[n_thr]
    while stop condition in False do
        for each active thread do
        # pragma omp task
            int id
            centroidsVec priv_centr
            Divide points in n_thr-blocks
            for each point in block do
                for each centroid do
                    Find min distance
                end for
                Update priv_centr[closer centr]
            end for
            Update master_centr[id] with
                                   priv_centr data
        end for
        # pragma omp taskwait

        Evaluate new centroids
        centroids ← new centroids
    end while
```

Algorithm 2 K-means SV(points, centroids, n_thr)

```
double x[k], y[k]
int n_points[k]
# pragma omp parallel num_threads(n_thr)
while stop condition is False do
    # pragma omp for reduction on x, y, n_points
    for all points do
        for all centroids do
            Find the min distance
        end for
        Update x, y, n_points of the closer centr
    end for
    # pragma omp barrier

    # pragma omp single
        Evaluate new centroids
        centroids ← new centroids
end while
```

4 Utilized CPU

Following results were collected using the CPU AMD Ryzen 7 3750H. Here we report same characteristics:

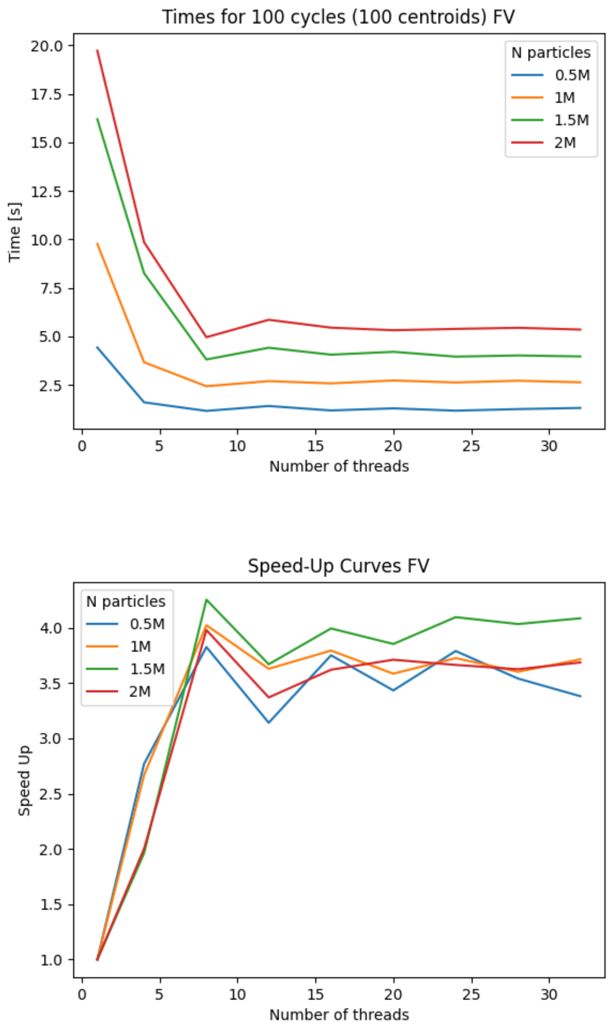
- number of cores: 4
- number of flows: 8
- Frequency: 2.3 GHz
- L1 Cache: 384 KB
- L2 Cache: 2 MB
- L3 Cache: 4 MB

5 Results

In Figure 2 and in Figure 3 time results are reported (times for 100 iterations of while loop). They were taken by changing the number of particles N and the number of active thread n_thr. Speed up curves are evaluated using times of the sequential version (only one active thread) as reference.

6 Conclusions

Plots show the performance of the algorithm, when the number of particles and the number of active thread change. As we can see, both versions of the algorithm have similar performance. Speed-up increases when n_thr $\in [1, 8]$ and it reaches the maximum for n_thr $= 8$ (speed-up ≈ 4). When n_thr > 8, overhead effects decrease performance.
Note that, in general, the first version of the algorithm achieves slightly higher performance than the second version.



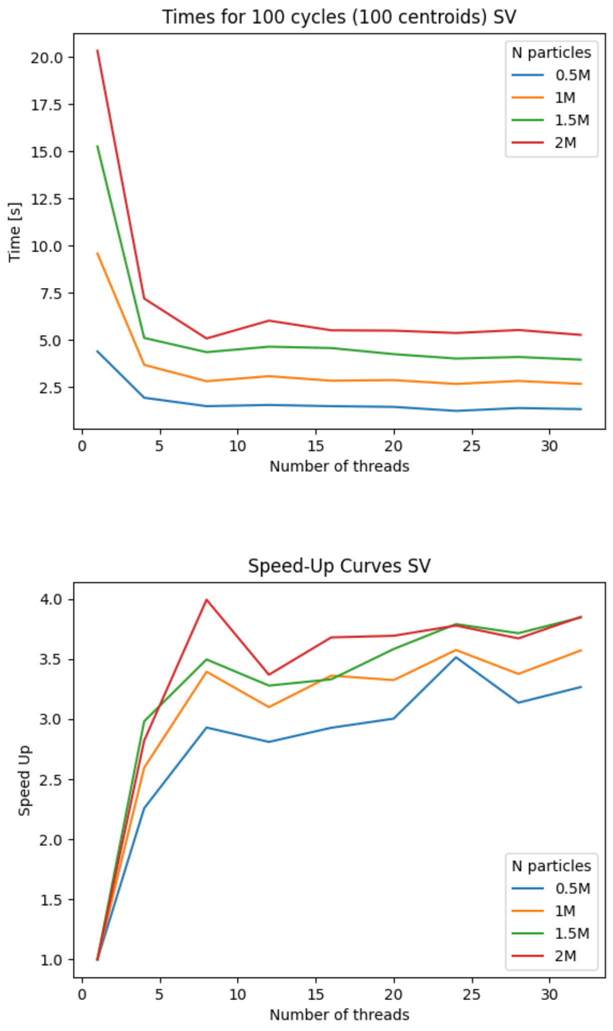


Figure 2: Times and speed-up of the FV algorithms.

Figure 3: Times and speed-up of the SV algorithms.