

Mean shift clustering algorithm

comparison between sequential, openMP and CUDA implementations

Parallel Computing (9 CFU)

Francesca Del Lungo and Matteo Petrone

Prof. Marco Bertini

January 2021



Contents overview

1 Introduction

2 Implementation

3 Experiments

4 Conclusions

Introduction

Mean Shift

- Non-parametric **clustering** procedure
- Computational Complexity: $\mathcal{O}(n^2)$.
- **Embarrassingly parallel** structure

Mean Shift

- It builds upon the concept of **kernel density estimation** (KDE).
- At each step of the procedure a kernel function is applied to each point that causes the points to shift in the direction of the nearest peak of the KDE surface:

$$K(x) = e^{-\frac{x^2}{2\sigma^2}} \quad (1)$$

where x : distance, σ : *bandwidth*.

Implementation

Sequential Version

Algorithm 1 Mean shift algorithm

```
procedure MEANSHIFT(original_points)  
  shifted_points  $\leftarrow$  original_points  
  while iteration < N_ITERATIONS do  
    for point in shifted_points do  
      point  $\leftarrow$  SHIFTPPOINT(point, original_points)
```

Implemented in C++

Sequential Version

Algorithm 2 Mean shift subroutine

procedure SHIFTPoint(*point*, *original_points*)

$num \leftarrow 0$

$den \leftarrow 0$

for *op* **in** *original_points* **do**

$dist \leftarrow \text{COMPUTEDISTANCE}(point, op)$

$w \leftarrow \text{KERNEL}(dist, BANDWIDTH)$

$num \leftarrow num + op * w$

$den \leftarrow den + w$

return num/den

Parallel Version: OpenMP

- OpenMP (Open Multiprocessing) is an API for shared-memory parallel programming.
- It follows the the **fork-join** programming model.
- It does not require program restructuring, but only the addition of **compiler directives**

Parallel Version: OpenMP

Algorithm 3 Mean shift openMP algorithm

```
procedure OMPMEANSHIFT(original_points)  
  shifted_points  $\leftarrow$  original_points  
  while iteration < N_ITERATIONS do  
    #pragma omp parallel for schedule(static)  
    for point in shifted_points do  
      point  $\leftarrow$  SHIFTPOINT(point, original_points)
```

Parallel Version: CUDA naive

- Each Point to be shifted assigned to a thread.
- **Coalesced access** to global memory: points are stored as *Structure of Arrays* $[x_1, \dots, x_n, y_1, \dots, y_n, z_1, \dots, z_n]$.
- Access to the array is done: $BlockDim.x * BlockIdx.x + threadIdx.x$.

Parallel Version: CUDA naive

Algorithm 4 CUDA naive kernel

procedure NAIVEKERNEL(*shifted_pts*, *orig_pts*)

$idx \leftarrow threadIdx.x + blockIdx.x * blockDim.x$

if $idx < |orig_pts|$ **then**

$sp \leftarrow shifted_pts[idx]$

$tot_weight \leftarrow 0$

$new_spt \leftarrow 0$

for op **in** $orig_pts$ **do**

$dist \leftarrow \text{COMPUTEDISTANCE}(op, sp)$

$weight \leftarrow \text{KERNEL}(dist, BW)$

$new_spt \leftarrow new_spt + op * weight$

$tot_weight \leftarrow tot_weight + weight$

$shifted_pts[idx] \leftarrow new_spt / tot_weight$

Parallel Version: CUDA Tiling

- Limit global memory access making use of shared memory

Algorithm 5 CUDA kernel tiling - data loading

```
tile  $\leftarrow$  shared_mem_array[TILE_WIDTH]  
n_tiles  $\leftarrow$  ( $|orig\_pts| - 1$ ) / (TILE_WIDTH + 1)  
for tile_i in n_tiles do  
    tile_idx  $\leftarrow$  tile_i * TILE_WIDTH + threadIdx.x  
    if tile_idx <  $|orig\_pts|$  then  
        tile[tx]  $\leftarrow$  orig_pts[tile_idx]  
    else  
        tile[tx]  $\leftarrow$  null_pt  
    __syncthreads()
```

Experiments

Dataset

- We generated sets of 3d points using *sklearn.dataset.make_blobs()*.
- It generates **gaussian distribution** with 3 centers and 1.5 standard deviation.
- Datasets dimensions: 100, 1.000, 10.000, 100.000, 500.000, 1.000.000.

Experiments setting

All the tests have been performed on a machine equipped with:

- CPU: Intel Core i7-860 @ 2.80GHz, with 4 cores/ 8 threads
- GPU: NVidia GeForce GTX 980, 4 GB (with CUDA 10.1)
- Average over 15 runs

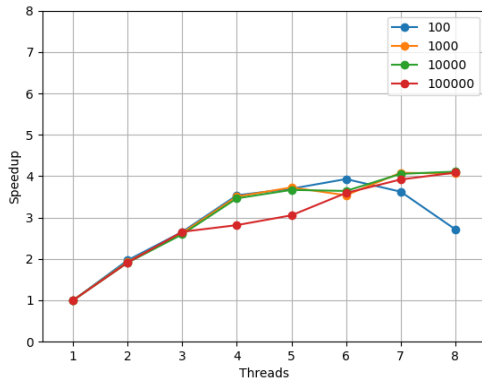
Speedup

To compare the performance of a sequential respect to a parallel implementation: **speedup** metric.

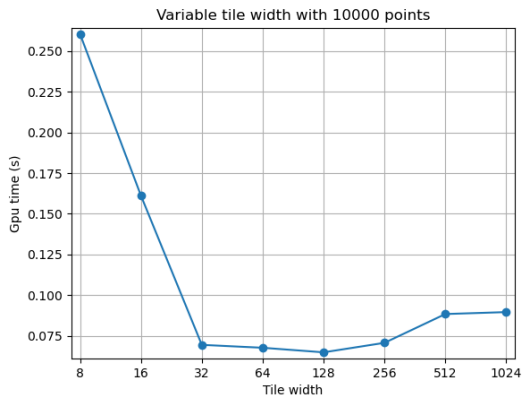
$$S = \frac{t_s}{t_p}$$

where t_s : sequential time execution, t_p : parallel time execution.

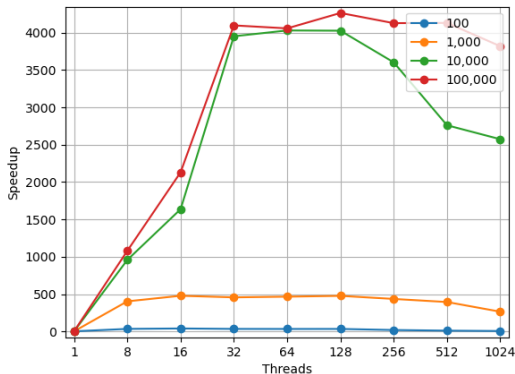
Speedup: Sequential over OpenMP



GPU Time varying tile width



Speedup: Sequential over CUDA



Conclusions

Conclusions

- Mean shift $\mathcal{O}(n^2)$, but **embarrassingly parallel** structure

OpenMP

- Implementation difficulty: very low
- Speedup: sub-linear

CUDA

- Implementation difficulty: higher
- Speedup: up to 4400x time faster.

Thanks for the attention