k-Nearest Neighbors algorithm: comparison between sequential, OpenMP and CUDA implementations

Iacopo Erpichini and Federico Magnolfi

University of Florence

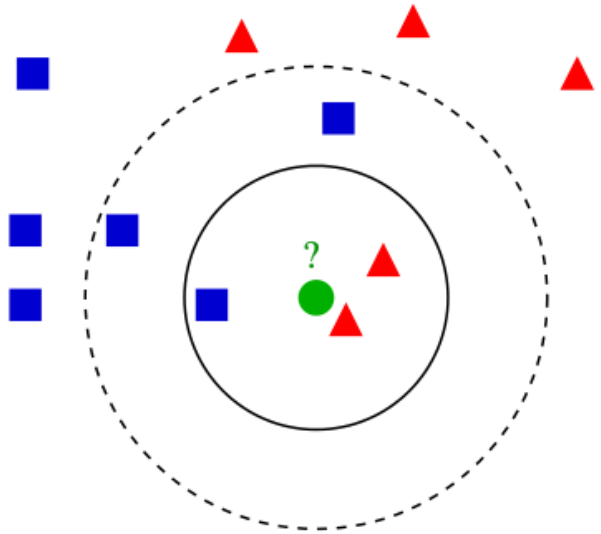
Outline

k-Nearest Neighbors problem

Given a dataset $\mathcal{D}$ of N points $x_i \in \mathbf{R}^n$, a test point $q \in \mathbf{R}^n$ and a distance measure d, the k-Nearest Neighbors problem (k-NN) is to find the k points closest to q in $\mathcal{D}$, i.e. find an ordered subset $\mathcal{S}$ of $\mathcal{D}$ such that:

- $\mathcal{S} = \{x_{i_1}, x_{i_2}, ..., x_{i_k}\}$
- $j < h \implies d(q, x_{i_j}) \leq d(q, x_{i_h})$
- $d(q, x_{i_j}) \leq d(q, x_m), \forall x_{i_j} \in \mathcal{S}, \forall x_m \in \mathcal{D} \setminus \mathcal{S}$

Example of k-NN problem



● : query

▲ ■ : dataset points

In this example, the neighbors have information (shape/color) that can be used for other tasks, such as classification/regression

Objective

Compare a sequential and two parallel versions of k-NN measuring:

- compute time
- speedup

while varying:

- number of threads
- dataset size

Dataset

We use the k-NN algorithm on a SIFT dataset

Dataset

Why k-NN it's important on SIFT data

- SIFT is a feature detection algorithm used in computer vision to detect and describe local features in images
- SIFT descriptors are 128-dimensional floating point vectors, used for image classification and object detection
- **k-NN** is used to find training SIFTs **"near/similar"** to the SIFTs in the test image

Sequential Implementation

Algorithm 1: k-Nearest Neighbors - Sequential version

Input : dataset, query, k
Output: nearestNeighbors

```
1  // init
2  indexes = new int[dataset.size]
3  distances = new float[dataset.size]
4  // calculate distances
5  for p from 0 to dataset.size-1 do
6      indexes[p] = p
7      distances[p] = euclideanDistance(query, dataset[p])
8  end
9  // sort by increasing distance
10 sortByKey(indexes, keys=distances)
11 // slice
12 nearestNeighbors = indexes[:k]
```

Open MP Implementation (1)

Algorithm 2: k-Nearest Neighbors - OpenMP version

Input : dataset, query, k, numThreads
Output: nearestNeighbors

```
1 // init
2 indexes = new int[dataset.size]
3 distances = new float[dataset.size]
4 // calculate distances

6 for p from 0 to dataset.size-1 do
7     indexes[p] = p
8     distances[p] = euclideanDistance(query, dataset[p])
9 end
```

Open MP Implementation (1)

Algorithm 3: k-Nearest Neighbors - OpenMP version

Input : dataset, query, k, numThreads
Output: nearestNeighbors

```
1 // init
2 indexes = new int[dataset.size]
3 distances = new float[dataset.size]
4 // calculate distances
5 # pragma omp parallel for
6 for p from 0 to dataset.size-1 do
7     indexes[p] = p
8     distances[p] = euclideanDistance(query, dataset[p])
9 end
```

Open MP Implementation (2)

```
10 chunkSize = dataset.size / numThreads
11 // sort chunks by increasing distance
12 # pragma omp parallel for
13 for j from 0 to numThreads-1 do
14 |   s = j * chunkSize
15 |   e = s + chunkSize
16 |   sortByKey(indexes[s:e], keys=distances[s:e])
17 end
```

Open MP Implementation (2)

```
10 chunkSize = dataset.size / numThreads
11 // sort chunks by increasing distance
12 # pragma omp parallel for
13 for j from 0 to numThreads-1 do
14 |   s = j * chunkSize
15 |   e = s + chunkSize
16 |   sortByKey(indexes[s:e], keys=distances[s:e])
17 end
18 // merge sorted chunks
19 for j from 1 to numThreads-1 do
20 |   i, d = indexes[:k], distances[:k]
21 |   s = j * chunkSize
22 |   e = s + k
23 |   indexes[:k], distances[:k] = merge(i,d,indexes[s:e],distances[s:e])
24 end
25 // slice
26 nearestNeighbors = indexes[:k]
```

Scheduling Open MP

OpenMP creates the threads and distributes the iterations between them depending on the **scheduling**, which can be:

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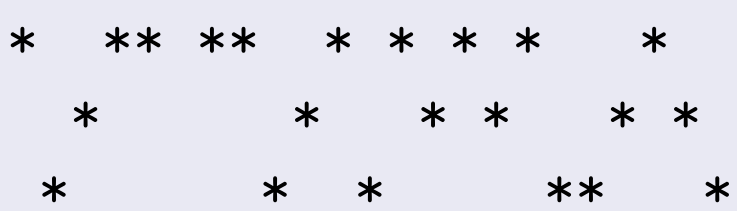
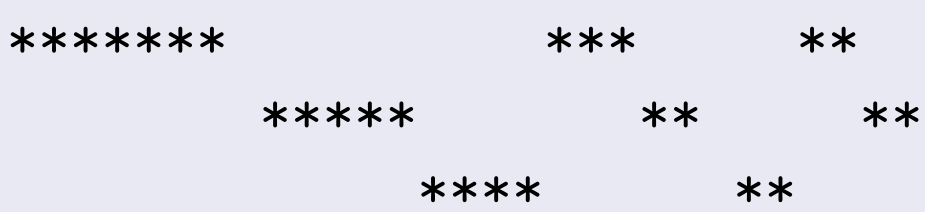


- `guided`: *decreasing-size chunks*, *available thread*



Scheduling Open MP

- `static`: *equal-sized chunks*, *circular order*

CUDA Implementation

Algorithm 4: k-Nearest Neighbors - CUDA version

Input : dataset, query as q, k, bSize
Output: nearestNeighbors

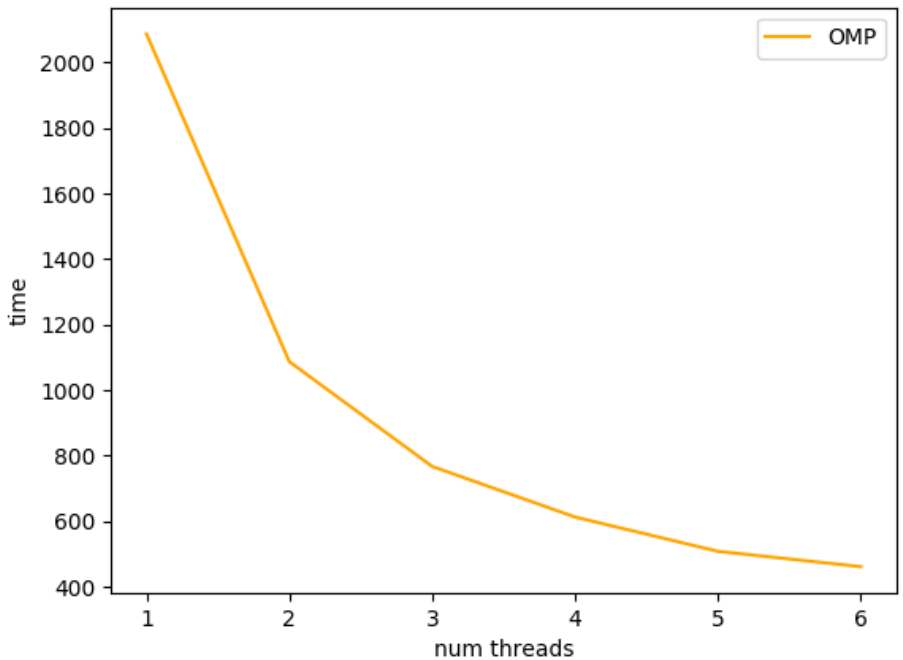
```
1  // init
2  indexes = new int[dataset.size]
3  distances = new float[dataset.size]
4  // move query to GPU memory
5  q = toGPU(q)
6  // determine number of blocks
7  blocks = (datasetSize + bSize - 1) / bSize
8  // calculate the distances
9  idxs, dists = cudaDistances<<<blocks,bSize>>>(dataset,q)
10 // sort by increasing distance on GPU
11 sortByKeyOnGPU(idxs, keys=dists)
12 // slice and move results to CPU memory
13 nearestNeighbors = toCPU(idxs[:k])
```

Test configuration

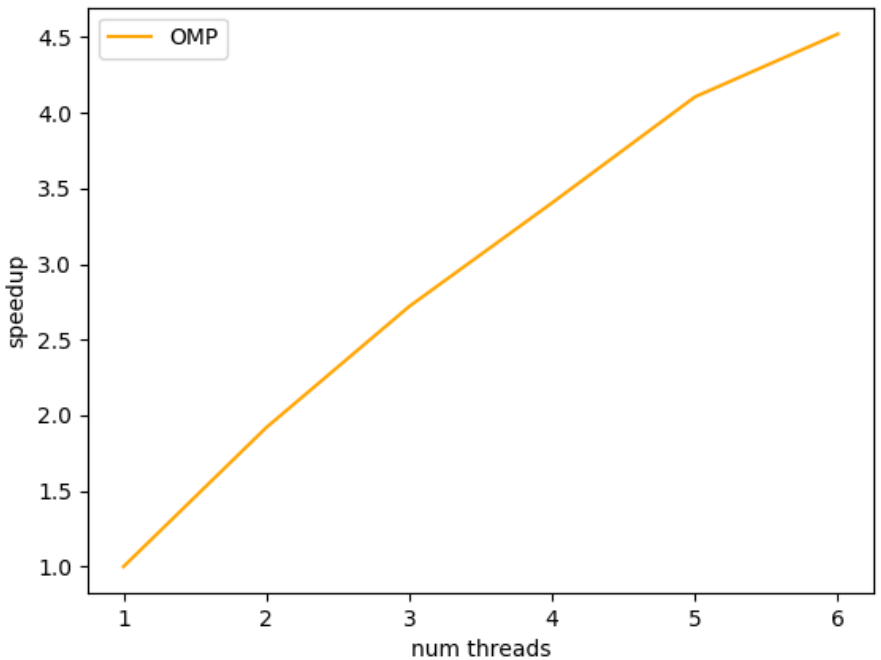
- CPU: Intel Core i7-8750H, 6 cores / 12 threads
- GPU: NVIDIA GeForce GTX 1050 Ti (Notebook), 768 CUDA cores, 4 GiB video RAM, 6 SM
- RAM: 16 GiB
- CUDA: 10.0
- OpenMP: 4.5

OpenMP

Evaluation time



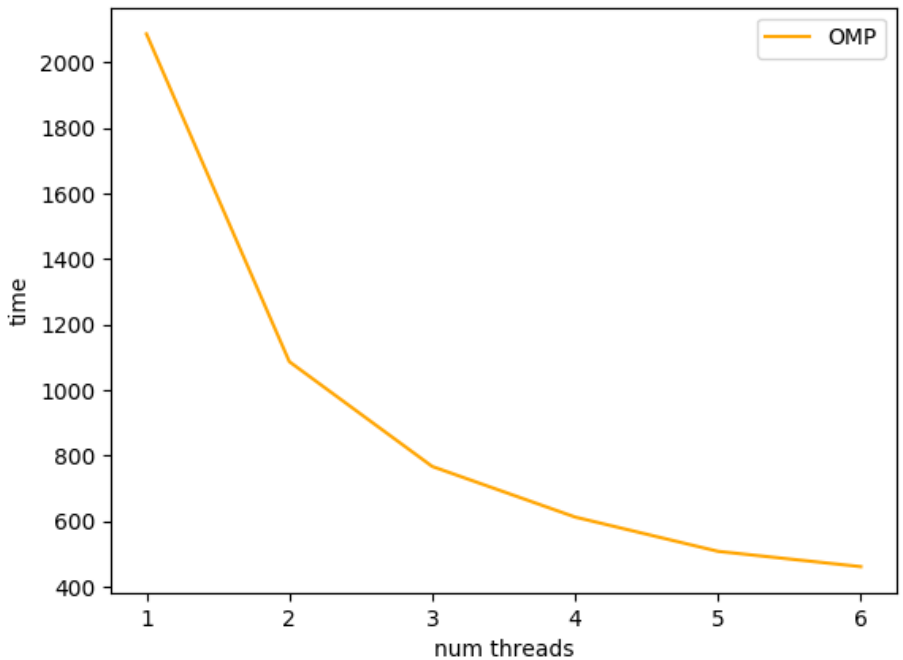
Speedup



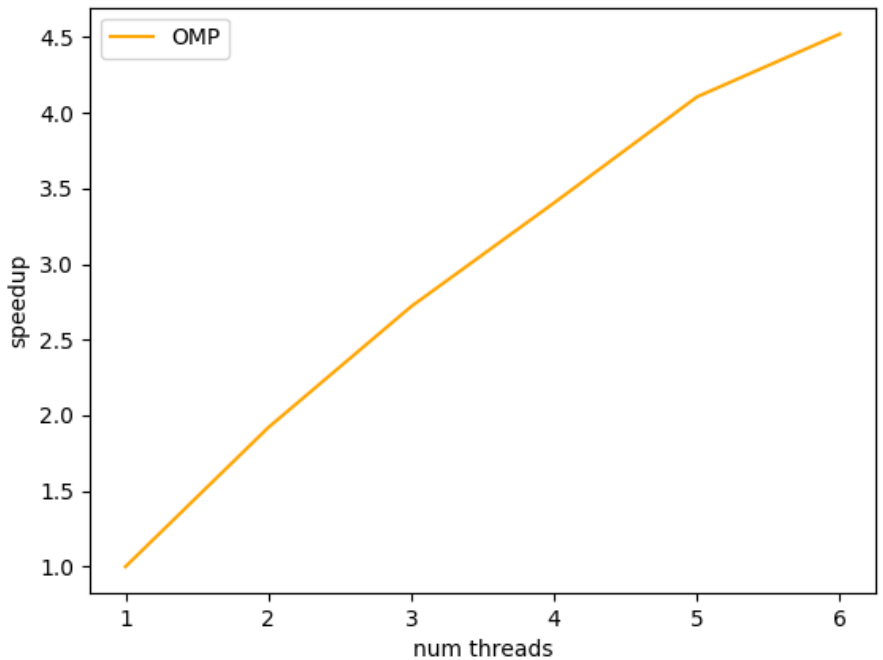
Plots in function of the number of threads

OpenMP

Evaluation time



Speedup

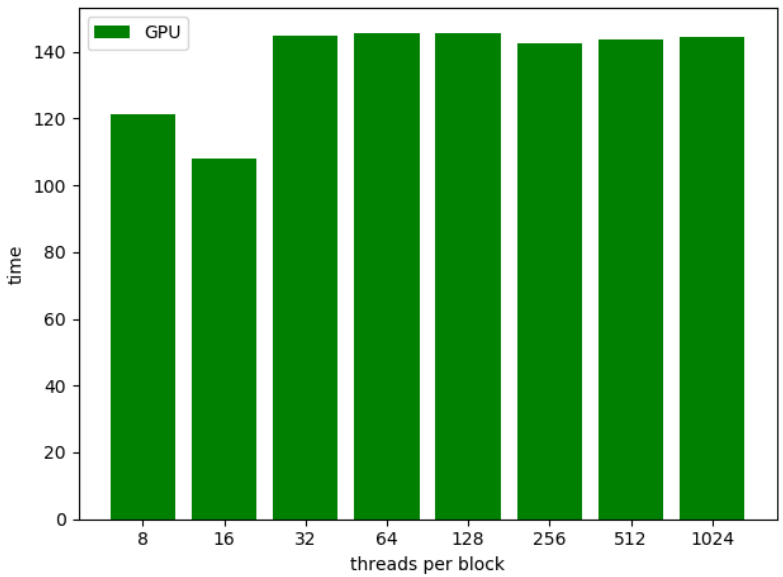


Plots in function of the number of threads

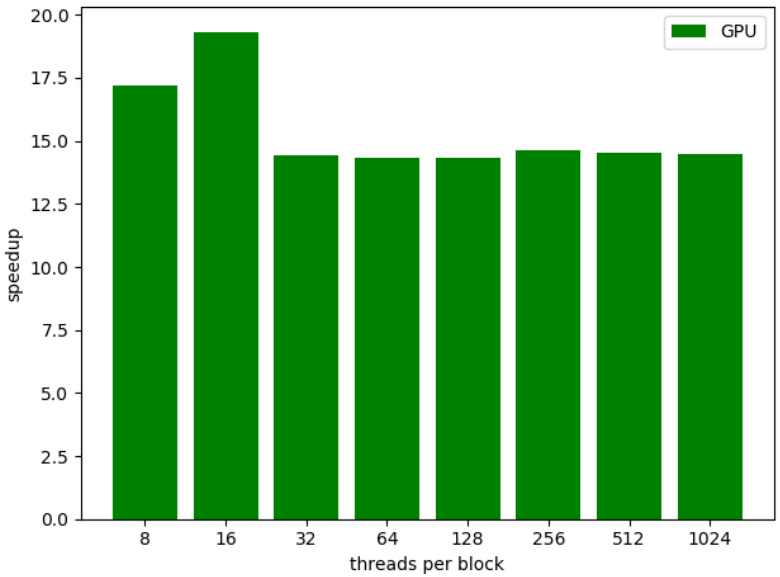
The obtained SpeedUp is sub-linear

CUDA

Evaluation time



Speedup



Plots in function of the number of threads per block

Observation on CUDA results

Best block size is 16

The block size in k-NN is not much relevant for the evaluation time.

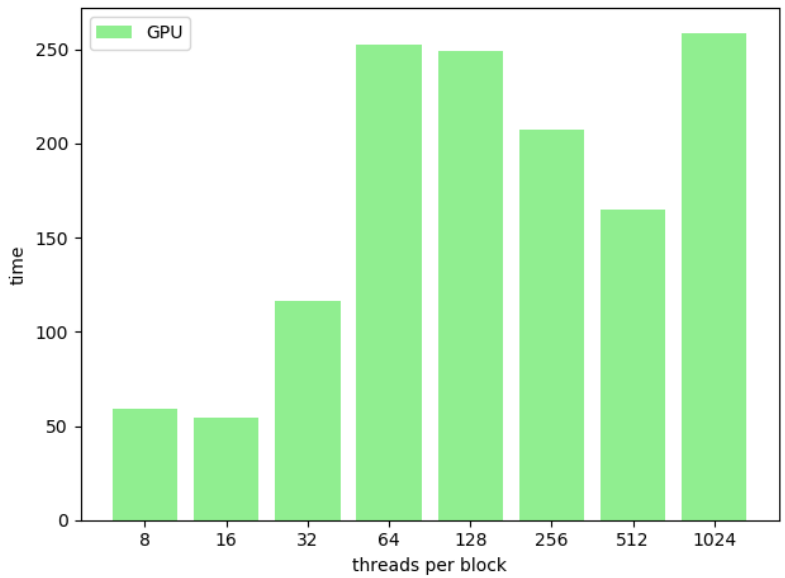
- GPU used in our tests has 6 *Streaming Multiprocessors* only
- Even with a big block size, it's easy to occupy every **SM**
- Distances calculation time $>$ data transfer $+$ sync time *

*: verified using Valgrind tools: `https://valgrind.org`

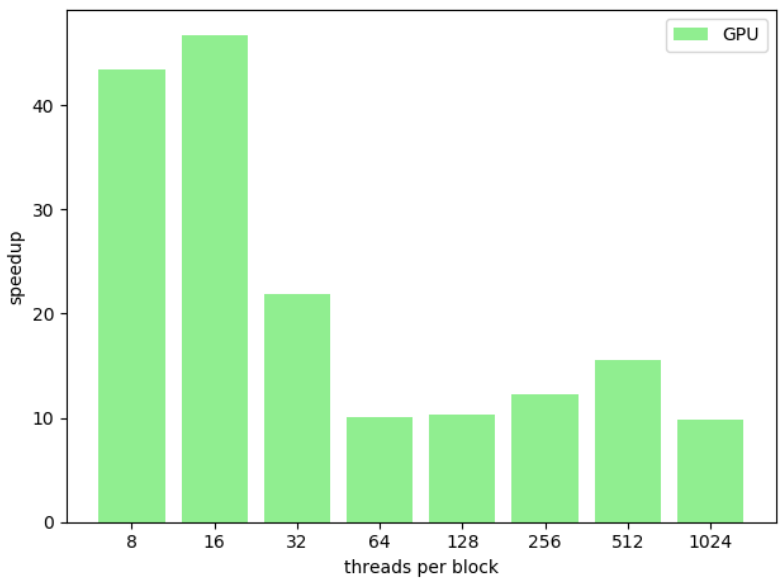
Other experiment on CUDA

To check if with a more powerful GPU the block size becomes important, we run the experiments on a NVIDIA GTX 980 GPU (which has 16 SM)

Evaluation time

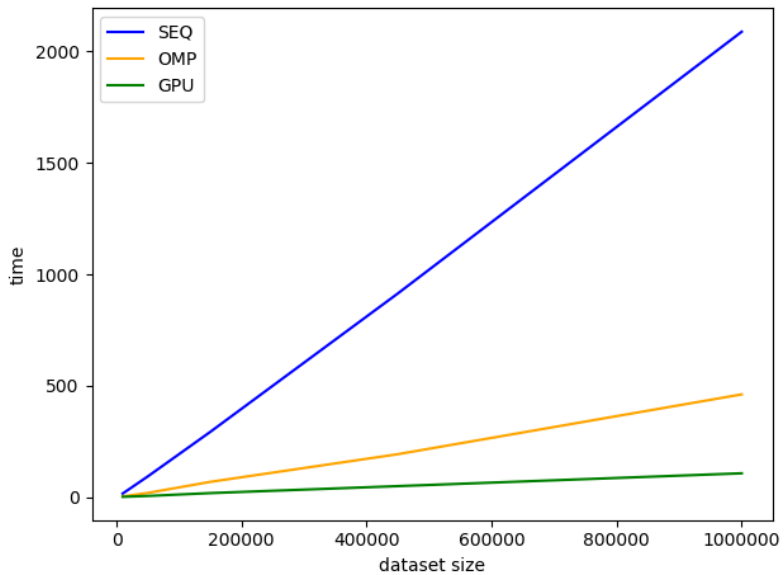


Speedup

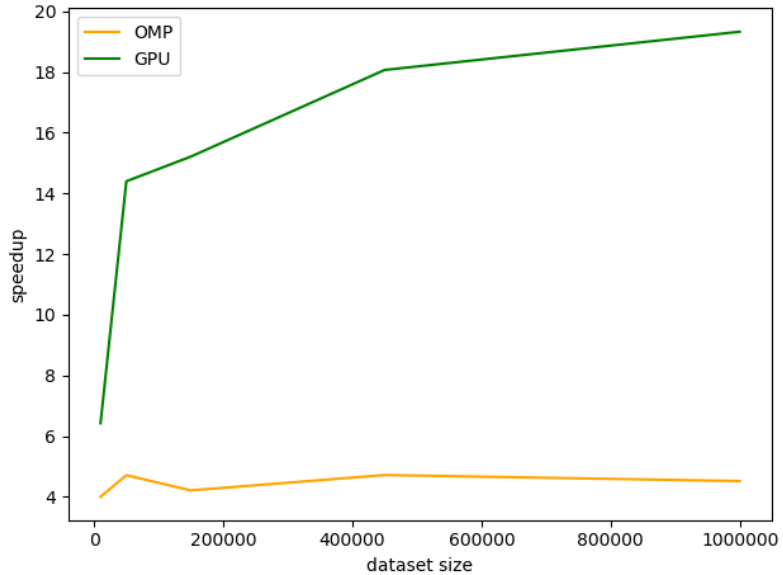


Comparison

Evaluation time



Speedup



Plots in function of the dataset size

OpenMP

- *Implementation difficulty*: low
- *Speedup*: sub-linear
- Makes parallel computing very accessible

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- *Speedup*: sub-linear
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CUDA

- *Implementation difficulty*: high
- *Speedup*: huge ($\sim$ 10-100)
- Highest level of single-machine parallelism

End

Thanks for the attention