Saint Petersburg National Research University of Information Technologies, Mechanics and Optics (ITMO University)
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REPORT

about laboratory work № 3

« The degree of objects similarity »

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Report

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1 Goal of laboratory work

The goal of this work is to implement a sequential and parallel k-means algorithm and compare the performance of the implemented algorithms.

2 Task Definition

1. Describe the parallel implementations of the DBSCAN and k-means algorithms in terms of parallel design.
2. Select a data set among those proposed (or any other) and implement the k-means serial and parallel algorithm, Compare the performance of implemented algorithms.

3 Brief Theory

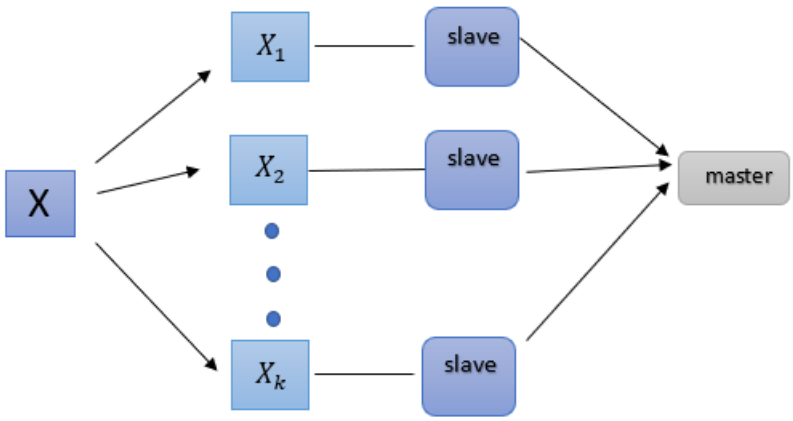
The task of clustering is to divide the original data sample into disjoint groups, and the objects from one group should have a similarity, which is most often characterized by a function of the distance between objects.

3.1 DBSCAN

DBSCAN (Density-based spatial clustering of applications with noise) is a clustering algorithm that allows you to find clusters of arbitrary shape in a metric space. The basic idea of the DBSCAN algorithm is to represent cluster objects as a group of points in a metric space, which are the vertices of a single connected graph.

DBSCAN , k-d tree, r-tree, vintage-point tree. X X_i, $i = 1, \ldots, k$.

The main feature of the parallel implementation of the DBSCAN algorithm is the master-slave architecture. The metric space is divided into areas and the calculations are distributed between the slave machines. Each of these areas is searched for clusters, and the need to merge with clusters from other areas is determined. Then the slave machines send the results of their calculations to the master machine, which merges the necessary clusters together and finishes the execution of the distributed algorithm. The scheme of this algorithm is shown in the figure below.



3.2 K-means

The k-means algorithm splits the set X into k sets $S_1, S_2, \ldots, S_k$, so as to minimize the sum of squares of distances from each point of the cluster to its center. The work of the algorithm consists of iteration, in each of which the distribution of d-dimensional vectors occurs over k clusters, as well as the recalculation of cluster centers in d-dimensional space. In the distribution step of d-dimensional vectors over k clusters, the distances between the vector and cluster centers are calculated independently, therefore they can be performed in parallel.

Then, dividing the entire calculation of distances into n streams, we obtain that in each stream only one operation will be performed to calculate the distance between the vectors. Moreover, the coordinates of the centers of all the clusters are transferred to each computational flow.

Cluster mass centers are also recalculated independently of each other, these operations can be performed in separate threads.

4 ALGORITHM (METHOD) of IMPLEMENTATION

[10]:
```
%cat example2.c
```

```
#include <math.h>
#include <stdio.h>
#include <stdlib.h>
#include <time.h>
#include <sys/time.h>


#include <assert.h>
#include <float.h>
#include <math.h>
#include <stdlib.h>
#include <stdio.h>
#include <string.h>
```

```
#include <omp.h>

#define KMEANS_NULL_CLUSTER -1

/*
* If the algorithm doesn't converge within this number of iterations,
* it will return with a failure error code.
*/
#define KMEANS_MAX_ITERATIONS 1000

#define kmeans_malloc(size) malloc(size)
#define kmeans_free(ptr) free(ptr)

typedef void * Pointer;

typedef enum {
        KMEANS_OK,
        KMEANS_EXCEEDED_MAX_ITERATIONS,
        KMEANS_ERROR
} kmeans_result;


typedef double (*kmeans_distance_method) (const Pointer a, const Pointer b);

typedef void (*kmeans_centroid_method) (const Pointer * objs, const int *
clusters, size_t num_objs, int cluster, Pointer centroid);

typedef struct kmeans_config
{
        /* Function returns the "distance" between any pair of objects */
        kmeans_distance_method distance_method;

        /* Function returns the "centroid" of a collection of objects */
        kmeans_centroid_method centroid_method;

        /* An array of objects to be analyzed. User allocates this array */
        /* and is responsible for freeing it. */
        /* For objects that are not capable of participating in the distance */
        /* calculations, but for which you still want included in the process */
        /* (for examples, database nulls, or geometry empties) use a NULL */
        /* value in this list. All NULL values will be returned in the */
        /* KMEANS_NULL_CLUSTER. */
        Pointer * objs;

        /* Number of objects in the preceding array */
        size_t num_objs;

        /* An array of inital centers for the algorithm */
```

```
        /* Can be randomly assigned, or using proportions, */
        /* unfortunately the algorithm is sensitive to starting */
        /* points, so using a "better" set of starting points */
        /* might be wise. User allocates and is responsible for freeing. */
        Pointer * centers;

        /* Number of means we are calculating, length of preceding array */
        unsigned int k;

        /* Maximum number of times to iterate the algorithm, or 0 for */
        /* library default */
        unsigned int max_iterations;

        /* Iteration counter */
        unsigned int total_iterations;

        /* Array to fill in with cluster numbers. User allocates and frees. */
        int * clusters;

} kmeans_config;

static void
update_r(kmeans_config *config)
{
        int i;

        #pragma omp parallel for
        for (i = 0; i < config->num_objs; i++)
        {
                double distance, curr_distance;
                int cluster, curr_cluster;
                Pointer obj;

                assert(config->objs != NULL);
                assert(config->num_objs > 0);
                assert(config->centers);
                assert(config->clusters);

                obj = config->objs[i];


                /*
                * Don't try to cluster NULL objects, just add them
                * to the "unclusterable cluster"
                */
                if (!obj)
                {
                        config->clusters[i] = KMEANS_NULL_CLUSTER;
```

```
                        continue;
                }
                // printf("It2\n");
                /* Initialize with distance to first cluster */
                curr_distance = (config->distance_method)(obj,
config->centers[0]);
                curr_cluster = 0;

                /* Check all other cluster centers and find the nearest */
                for (cluster = 1; cluster < config->k; cluster++)
                {
                        distance = (config->distance_method)(obj,
config->centers[cluster]);
                        if (distance < curr_distance)
                        {
                                curr_distance = distance;
                                curr_cluster = cluster;
                        }
                }

                /* Store the nearest cluster this object is in */
                config->clusters[i] = curr_cluster;
        }
}

static void
update_means(kmeans_config *config)
{
        int i;

        for (i = 0; i < config->k; i++)
        {
                /* Update the centroid for this cluster */
                (config->centroid_method)(config->objs, config->clusters,
config->num_objs, i, config->centers[i]);
        }
}



kmeans_result
kmeans(kmeans_config *config)
{
        int iterations = 0;
        int *clusters_last;
        size_t clusters_sz = sizeof(int)*config->num_objs;

        assert(config);
```

```
assert(config->objs);
assert(config->num_objs);
assert(config->distance_method);
assert(config->centroid_method);
assert(config->centers);
assert(config->k);
assert(config->clusters);
assert(config->k <= config->num_objs);

/* Zero out cluster numbers, just in case user forgets */
memset(config->clusters, 0, clusters_sz);

/* Set default max iterations if necessary */
if (!config->max_iterations)
        config->max_iterations = KMEANS_MAX_ITERATIONS;

/*
 * Previous cluster state array. At this time, r doesn't mean anything
 * but it's ok
 */
clusters_last = kmeans_malloc(clusters_sz);

while (1)
{
        /* Store the previous state of the clustering */
        memcpy(clusters_last, config->clusters, clusters_sz);

        update_r(config);
        update_means(config);
        /*
         * if all the cluster numbers are unchanged since last time,
         * we are at a stable solution, so we can stop here
         */
        if (memcmp(clusters_last, config->clusters, clusters_sz) == 0)
        {
                kmeans_free(clusters_last);
                config->total_iterations = iterations;
                return KMEANS_OK;
        }

        if (iterations++ > config->max_iterations)
        {
                kmeans_free(clusters_last);
                config->total_iterations = iterations;
                return KMEANS_EXCEEDED_MAX_ITERATIONS;
        }
}
```

```
        kmeans_free(clusters_last);
        config->total_iterations = iterations;
        return KMEANS_ERROR;
}

typedef struct point
{
        double x;
        double y;
} point;


static double pt_distance(const Pointer a, const Pointer b)
{
        point *pa = (point*)a;
        point *pb = (point*)b;

        double dx = (pa->x - pb->x);
        double dy = (pa->y - pb->y);

        return dx*dx + dy*dy;
}

static void pt_centroid(const Pointer * objs, const int * clusters, size_t
num_objs, int cluster, Pointer centroid)
{
        int i;
        int num_cluster = 0;
        point sum;
        double sum_x, sum_y;
        point **pts = (point**)objs;
        point *center = (point*)centroid;

        sum_x = sum_y = 0.0;

        if (num_objs <= 0) return;

        #pragma omp parallel for reduction(+:sum_x,sum_y,num_cluster)
        for (i = 0; i < num_objs; i++)
        {
                /* Only process objects of interest */
                if (clusters[i] != cluster) continue;

                sum_x += pts[i]->x;
                sum_y += pts[i]->y;
                num_cluster+=1;
        }
        if (num_cluster)
```

```
        {
                sum_x /= num_cluster;
                sum_y /= num_cluster;
                center->x = sum_x;
                center->y = sum_y;
        }
        return;
}

int
main(int nargs, char **args)
{
        kmeans_config config;
        kmeans_result result;
        int i, j;
        int spread = 3;
        point *pts;
        point *init;
        int print_results = 0;
        unsigned long start;

        int k = 10;


        srand(1234);

        /* Constants */
        config.k = k;
        config.num_objs = 100000; // config.k * nptsincluster;
        config.max_iterations = 200;
        config.distance_method = pt_distance;
        config.centroid_method = pt_centroid;

        /* Inputs for K-means */
        config.objs = calloc(config.num_objs, sizeof(Pointer));
        config.centers = calloc(config.k, sizeof(Pointer));
        config.clusters = calloc(config.num_objs, sizeof(int));

        /* Storage for raw data */
        pts = calloc(config.num_objs, sizeof(point));
        init = calloc(config.k, sizeof(point));

        /* Create test data! */
        /* Populate with K gaussian clusters of data */

        FILE *file = fopen("birch3.txt", "r");
        int n = 0, x, y;
        while ( fscanf(file, "    %d    %d\n", &x , &y) != EOF ) {
```

```
                pts[n].x = (double)x, pts[n].y = (double) y;
                config.objs[n] = &(pts[n]);

                n += 1;
                if( n > config.num_objs ) {
                        printf("Too many objects");
                        exit(1);
                }
        }

        /* Populate the initial means vector with random start points */
        for (i = 0; i < config.k; i++)
        {
                int r = floor(config.num_objs * (1.0 * rand() / RAND_MAX));
                /* Populate raw data */
                init[i] = pts[r];
                /* Pointers to raw data */
                config.centers[i] = &(init[i]);

                if (print_results)
                        printf("center[%d]\t%g\t%g\n", i, init[i].x, init[i].y);
        }

        /* run k-means! */
        start = time(NULL);
        result = kmeans(&config);

        printf("\n");
        printf("Iteration count: %d\n", config.total_iterations);
        printf("     Time taken: %ld seconds\n", (time(NULL) - start));
        printf(" Iterations/sec: %.3g\n",
(1.0*config.total_iterations)/(time(NULL) - start));
        printf("\n");

        /* print results */
        if (print_results)
        {
                for (i = 0; i < config.num_objs; i++)
                {
                        point *pt = (point*)(config.objs[i]);

                        if (config.objs[i])
                                printf("%g\t%g\t%d\n", pt->x, pt->y,
config.clusters[i]);
                        else
                                printf("N\tN\t%d\n", config.clusters[i]);
                }
        }
```

```
        free(config.objs);
        free(config.clusters);
        free(config.centers);

        free(init);
        free(pts);

}
```

5 Result And Experiments

Clusterization is performed on the `birch3.txt` dataset from the http://cs.joensuu.fi/sipu/datasets/ website. We test how the number of threads affects the clusterization speed.

[6]:
```
import subprocess
import os
from pathlib import Path

if Path('kmeans').exists():
    %cd kmeans/

def compile():

    _cmd = 'make -B example2'.split()
    # print(' '.join(_cmd))
    cmd = subprocess.run(_cmd, stdout=subprocess.PIPE, stderr=subprocess.PIPE)

    # if(cmd.stdout): print('cmd.stdout', cmd.stdout)
    if(cmd.stderr): print('cmd.stderr', cmd.stderr)

def run(env=None):
    cmd = subprocess.run('./example2', stdout=subprocess.PIPE,␣
 ↪stderr=subprocess.PIPE, env=env)
```

[7]:
```
compile()

for th in [1, 2, 4, 8, 16]:
    env = os.environ.copy()
    env['OMP_NUM_THREADS'] = str(th)

    print(f"Executing kmeans with {th} threads", end="\n\t")
    %timeit run(env)
    print()
```

```
Executing kmeans with 1 threads
        526 ms ś 58.6 ms per loop (mean ś std. dev. of 7 runs, 1 loop each)

Executing kmeans with 2 threads
        277 ms ś 3.37 ms per loop (mean ś std. dev. of 7 runs, 1 loop each)

Executing kmeans with 4 threads
        169 ms ś 7.52 ms per loop (mean ś std. dev. of 7 runs, 1 loop each)

Executing kmeans with 8 threads
        214 ms ś 125 ms per loop (mean ś std. dev. of 7 runs, 1 loop each)

Executing kmeans with 16 threads
        215 ms ś 17 ms per loop (mean ś std. dev. of 7 runs, 10 loops each)
```

6 Conclusion

In this paper, k-means sequential and parallel clustering algorithms were implemented and tested on a real word dataset. The skill of using clustering methods and the OpenMP library was gained.