

## Basics of Parallel Computing 2024S Assignment 2

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## 1 Exercise 1

```
#include <stdio.h>
#include <stdlib.h>
#include <omp.h>
int main(int argc, char *argv[]) {
   int nenv = 3;
   omp_set_num_threads(nenv); // set number of threads
   printf("nenv: %d\n", nenv);
   int chunk = 5;
   omp_set_schedule(omp_sched_static, chunk);
   // omp_set_schedule(omp_sched_dynamic, chunk);
   // omp_set_schedule(omp_sched_guided, chunk);
   printf("chunk size: %d\n", chunk);
   int i = 0;
   int n = 17;
   int a[n];
   int t[nenv];
   #pragma omp parallel for schedule(runtime)
   for (i=0; i<n; i++) {
       a[i] = omp_get_thread_num(); // chosen thread per iteration
       t[omp_get_thread_num()]++; // parallel increment
   printf("a (schedule): ");
   for (i=0; i<n; i++) {
       printf("%d ", a[i]);
   printf("\n");
   printf("t (counter): ");
   for (i=0; i<nenv; i++) {
       printf("%d ", t[i]);
   printf("\n");
}
```

## 1.1 What do a and t count?

The variable a stores the selected thread number for each parallel iteration, while t stores a non-atomic counter that all threads with the same ID increment. Unless no two threads are assigned the same iteration, the final value of t will be non-deterministic as each var++ operation is in fact a read-modify-write operation:

```
movl -4(%rbp), %eax # load var into eax addl $1, %eax # increment eax by 1 movl %eax, -4(%rbp) # store eax back into var
```

## 1.2 Values for all elements in a and t

See Tables 1 and 2 for the values of a and  ${\tt t}$  for different scheduling strategies.

Table 1: Values of array a for different scheduling strategies

							_					0	0				
case / a	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
static, 0	0	0	0	0	0	0	1	1	1	1	1	1	2	2	2	2	2
static, 1	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2	0	1
dynamic, 1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
dynamic, 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
guided, 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 2: Values of array t for different scheduling strategies - keep in mind that these values are not reproducible / deterministic.

case / t	0	1	2
static, 0	74307862	7	1806905557
static, 1	8591638	7	1872621781
dynamic, 1	6150416	18	1875062992
dynamic, 2	40737057	1	1840476368
guided, 5	51370273	1	1829843168

#### 2 Exercise 2

Table 3: Duration of independent tasks we want to schedule optimally.

Task ID	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Task duration	1	2	1	2	1	2	1	2	1	2	1	2	1	2	4	3	3

#### 2.1 Optimal Schedule

To minimize the total execution time with 4 workers, we can use the "Longest Processing Time" (LPT) algorithm by R. L. Graham in 1969. Here's how it works: First, sort the tasks by duration in descending order. Then, assign the tasks to the workers in a round-robin fashion. But beware that the LPT isn't guaranteed to find the optimal solution, but just to have a provable upper bound of  $\lceil 4/3 \cdot \text{OPT} \rceil$  where OPT is the optimal solution.

Assuming that tasks can be interrupted and resumed at any time, we can calculate the OTP as follows: OPT =  $\lceil \sum_{i=0}^{16} \text{task duration}_i/4 \rceil = \lceil 31/4 \rceil = 8$ .

Fortunately we were able to find one of the optimal solutions by using the LPT algorithm.

```
from itertools import groupby
from operator import itemgetter
def schedule_tasks(task_durations):
   sorted_tasks = sorted(enumerate(task_durations), key=lambda x: x[1], reverse=True) # fst: task_id, snd: duration
   worker_utilization = [0] * 4 # time spent on work by each worker so far
   scheduled_tasks = []
   for task_id, duration in sorted_tasks:
       # get least utilized worker
       min_time = min(worker_utilization)
       worker_index = worker_utilization.index(min_time)
       # assign task
       worker_utilization[worker_index] += duration
       # keep track of assigned task
       start_time = min_time
       end_time = start_time + duration
       scheduled_tasks.append((worker_index, task_id, start_time, end_time))
   return scheduled_tasks
task_durations = [1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 4, 3, 3]
print(f"sorted tasks: {sorted(task_durations, reverse=True)}\n")
scheduled_tasks = schedule_tasks(task_durations)
# group tasks by worker
scheduled_tasks.sort(key=itemgetter(0))
for worker, tasks in groupby(scheduled_tasks, key=itemgetter(0)):
   print(f"worker {worker}:")
   for task in tasks:
        print(f"\{task[1]\}, start: \{task[2]\}, end: \{task[3]\} (duration: \{task[3] - task[2]\})") 
   print()
# effective time
print(f"time spent: {max(map(itemgetter(3), scheduled_tasks))}")
```

```
sorted tasks: [4, 3, 3, 2, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1]

worker 0:
    task 14, start: 0, end: 4 (duration: 4)
    task 9, start: 4, end: 6 (duration: 2)
    task 2, start: 6, end: 7 (duration: 1)
    task 8, start: 7, end: 8 (duration: 1)

worker 1:
    task 15, start: 0, end: 3 (duration: 3)
    task 5, start: 3, end: 5 (duration: 2)
    task 13, start: 5, end: 7 (duration: 2)
    task 10, start: 7, end: 8 (duration: 1)
```

```
worker 2:
    task 16, start: 0, end: 3 (duration: 3)
    task 7, start: 3, end: 5 (duration: 2)
    task 0, start: 5, end: 6 (duration: 1)
    task 4, start: 6, end: 7 (duration: 1)
    task 12, start: 7, end: 8 (duration: 1)

worker 3:
    task 1, start: 0, end: 2 (duration: 2)
    task 3, start: 2, end: 4 (duration: 2)
    task 11, start: 4, end: 6 (duration: 2)
    task 6, start: 6, end: 7 (duration: 1)
```

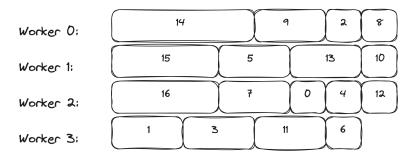


Figure 1: Gantt chart of the LPT schedule (which happens to be optimal).

# 2.2 Schedule static,3

The schedule static, 3 assigns each task to a worker in a round-robin fashion with a chunk size of 3.

The makespan of the schedule static, 3 is 11, which is suboptimal compared to the LPT schedule. The Gantt chart in Figure 2 shows the schedule.

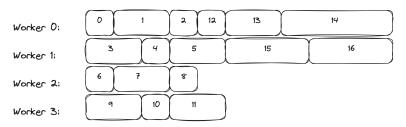


Figure 2: Gantt chart of the schedule static, 3.

### 2.3 Schedule dynamic, 2



Figure 3: Gantt chart of the schedule dynamic, 2.

# 3 Exercise 3

- $3.1\,$  Fix the problems with this OpenMP code
- 4 Exercise 4
- 4.1 What is the output of the three different versions?
- 4.2 How often is the function omp\_tasks called?
- 5 Exercise 5
- 5.1 Parallelize the pixel computation
- 5.2 Running time analysis
- 5.3 Influence of schedule parameter
- 6 Exercise 6
- 6.1 Parallelize the filter computation
- 6.2 Strong scaling analysis
- 6.3 Weak scaling analysis

# 7 Addendum: Raw Data

1168	1	1	0.0603872
1168	1	1	0.0607409
1168	1	1	0.0600319
1168	2	1	0.196807
1168	2	1	0.2452
1168	2	1	0.19003
1168	4	1	3.45923
1168	4	1	3.90704
1168	4	1	3.45583
1168	8	1	5.395
1168	8	1	5.45436
1168	8	1	4.53896
1168	16	1	10.7055
1168	16	1	10.5507
1168	16	1	10.2593
1168	24	1	17.3402
1168	24	1	18.5362
1168	24	1	17.2604
1168	32	1	26.1056
1168	32	1	25.1663
1168	32	1	27.9486

Figure 4: Raw output from "filter strong" job.

1168	1	1	0.060196
1168	1	1	0.0609
1168	1	1	0.060195
1168	2	2	0.401089
1168	2	2	0.635222
1168	2	2	1.18221
1168	4	4	14.4383
1168	4	4	13.3359
1168	4	4	9.2267
1168	8	8	44.0875
1168	8	8	44.8141
1168	8	8	42.5354

 $Figure \ 5: Raw\ output\ from\ "weak\ scaling"\ job.\ Timed\ out\ on\ \textit{slurmstepd}\ due\ to\ time\ out\ /\ time\ limit.$ 

90	1	0.110155
90	1	0.109749
90	1	0.109885
90	2	0.056617
90	2	0.056599
90	2	0.056612
90	4	0.045880
90	4	0.045966
90	4	0.045863
90	8	0.031120
90	8	0.031132
90	8	0.031170
90	16	0.018182
90	16	0.018227
90	16	0.018220
90	24	0.013238
90	24	0.013257
90	24	0.013180
90	32	0.014816
90	32	0.017296
90	32	0.014814
1100	1	16.306608
1100	1	16.316588
1100	1	16.284397
1100	2	8.175213
1100	2	8.178992
1100	2	8.170321
1100	4	6.621239
1100	4	6.678632
1100	4	6.639713
1100	8	4.557337
1100	8	4.554004
1100	8	4.586490
1100	16	2.447131
1100	16	2.448894
1100	16	2.447200
1100	24	1.731222
1100	24	1.718731
1100	24	1.718424
1100	32	1.312658
1100	32	1.313263
1100	32	1.320209

Figure 6: Raw output from "juliap" job.

"static"	1100	16	2.450491
"static"	1100	16	2.448260
"static"	1100	16	2.449136

Figure 7: Raw output from "juliap2" job.