Assignment 2 Profiling of Project

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Problem Statement

The travelling salesman problem, popularly known as TSP is an np-hard problem of finding a minimum Hamiltonian cycle on a complete graph with non-negative edges. A Hamiltonian cycle is a cycle that visits each node of the graph exactly once.

Why is the problem important?

The Travelling Salesman Problem is considered to be the holy-grail of computational problems. It has tremendous applications in real-life & therefore there's a need to solve the problem optimally.

Computational Complexity

Given n cities, there exist as many as (n-1)! / 2 hamiltonian cycles which implies the no. of possible solutions to the TSP problem when no. of cities = 100 is of the order 10 157 which is much much larger than the no. of particles in the universe.

Genetic Algorithms

In computer science and operations research, a genetic algorithm (GA) is a metaheuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA). Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems by relying on biologically inspired operators such as mutation, crossover and selection.

Pseudo - Code for Genetic Algorithm

The Algorithm

GENETIC-ALGORITHM()

- 1 P ← create N candidate solutions ▷ initial population
- 2 repeat
- 3 compute fitness value for each member of P
- 4 S ← with probability proportional to fitness value, randomly select N members from P
- offspring ← partition S into two halves, and randomly mate and crossover members to generate N offsprings
- 6 with a low probability mutate some offsprings
- 7 replace k weakest members of P with k strongest offsprings
- 8 until some termination criteria
- 9 return the best member of P

Serial Code:

The code is too long and has been omitted from the report. It can be accessed through the following github repository:

https://github.com/hello-fri-end/Parallel-Implementation-of-Genetic-Algorithms-for-TSP

Functional Profiling Results

Showing only the top results. The file can also be accessed through the github repository.

```
Flat profile:

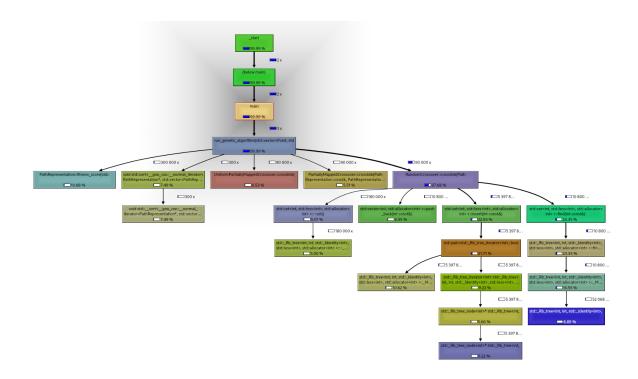
Each sample counts as 0.01 seconds.
% cumulative self self total
time seconds seconds calls ms/call ms/call name
5.02 0.12 0.12 110096318 0.00 0.00 std::vector<int, std::allocator<int>
>::operator[](unsigned long)
3.98 0.22 0.10 18000000 0.00 0.00 Point::distance_to(Point const&) const
3.77 0.31 0.09 93773710 0.00 0.00 std::Rb_tree<int, int, std::_Identity<int>,
std::less<int>, std::allocator<int>>::_S_key(std::Rb_tree_node<int>> const*)
3.77 0.40 0.09 5396103 0.00 0.00 std::Rb_tree<int, int, std::_Identity<int>,
std::less<int>, std::allocator<int>>::_M_get_insert_unique_pos(int const&)
3.35 0.48 0.08 5396103 0.00 0.00 std::Rb_tree<int int, std::_Rb_tree<int, int, std::_Identity<int>, std::_Rb_tree<int, int, std::_Rb_tree<int, int, std::_Identity<int>, std::_Identity<int>, std::_Rb_tree<int, int, std::_Identity<int>, std::_Identity<int>,
```

Call Graph:

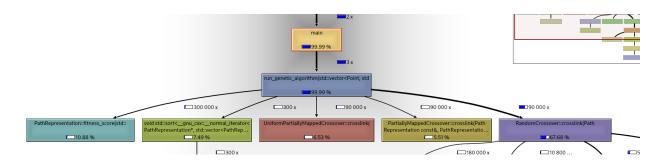
```
Call graph (explanation follows)
                                                                run_genetic_algorithm(std::vector<Point,</pre>
std::allocator<Point> > const&, Crossover*, unsigned long, unsigned long, unsigned long, unsigned long)
0.00 0.00 183/11340183 bool __gnu_cxx::operator!=<int*, std::vector<int, std::allocator<int> > (__gnu_cxx::__normal_iterator<int*, std::vector<int, std::allocator<int> > const&, __gnu_cxx::__normal_iterator<int*, std::vector<int, std::allocator<int> > > const&) [60]
                                                                 PathRepresentation::get_order() const [76] 
__gnu_cxx::_normal_iterator<int*, std::vector<int,
std::allocator<int> > >::operator*() const [124]
                                                                 PathRepresentation::~PathRepresentation() [106]
                                                                  std::vector<int, std::allocator<int> >::end() [116]
                                                                 PathRepresentation::get_fitness_score() const [127] std::vector<int, std::allocator<int> >::begin() [146]
                                                                 Point::Point(double, double, double) [299]
Point::~Point() [288]
std::vector<Point, std::allocator<Point> >::vector()
[362]
                               0.00
                                                                 RandomCrossover() [347]
                                                                 PartiallyMappedCrossover::PartiallyMappedCrossover()
UniformPartiallyMappedCrossover::UniformPartiallyMappedCrossover() [351]
UniformPartiallyMappedCrossover::~UniformPartiallyMappedCrossover() [352]
                                                                 PartiallyMappedCrossover::~PartiallyMappedCrossover()
                                                                 RandomCrossover::~RandomCrossover() [348]
```

Call Graph:

Note that the graph obtained using gprof2dot wasn't readable. I used valgrind and & k-cache-grind to obtain the below call graph.



Using kcachegrind, let's zoom into the call-graph & find where maximum percentage of the time is taken:



Let's analyze the call graph:

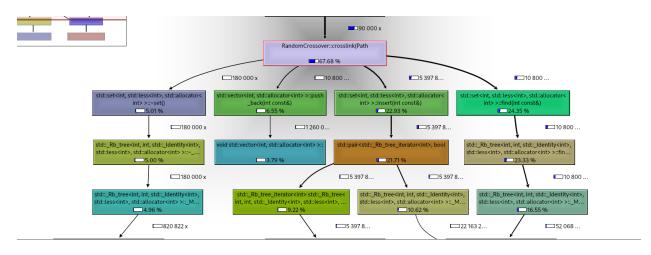
 Fitness_Score: This function is called for every new generation & computes the fitness_value (path length) of every genome in the population.

Optimizations possible:

 The function uses distances_to method calculates the distance between the points. We can store the distances which have been calculated so that we won't have to calculate them again. 2. Sort: This standard template library function is used to sort the fitness scores. It is called after every new generation.

Optimizations possible:

- Instead of calling this function after every generation. It can be called only once during the first iteration & for every new iteration we can use insertion_sort to insert the crosslinked genome into the population. This will reduce the complexity from O(nlogn) to O(kn).
- 3. Crossovers: Among the crossovers, it can be seen that random_crossover takes the highest amount of time. Let's further visualize the call graph of random_crossover



The highest amount of time is taken by vector.find() function which can be optimized by using a map.

Line - Based Profiling Results:

The output of line based profiling is shared in the link below:

Process Resource Utilization Report:

roup 1: L3				
Event	Counter	HWThread 0	HWThread 1	HWThread 2
INSTR_RETIRED_ANY	FIXC0	231330	 4137	 0
CPU_CLK_UNHALTED_CORE	FIXC1	321123	23341	0
CPU_CLK_UNHALTED_REF	FIXC2	723750	52800	0
L2_LINES_IN_ALL	PMC0	9065	690	0
L2_TRANS_L2_WB	PMC1	2507	58	0

+		HWThread 0		/Thread 1	HWThread 2	+
,		0.0012	! !	0.0012	0.001	
Runtime unhalted [s] Clock [MHz] 79		0.0002 98.6444	1.296728e-05 795.7124		()
		1.3882	¦ .	5.6420	_	+
		74.2809	36.1008		() i
L3 load data volume [GBytes]		0.0006	4.416000e-05		() į
L3 evict bandwidth [MBytes/s]	13	31.1663	!	3.0346	!	
L3 evict data volume [GBytes]	0.0002 605.4471					
L3 bandwidth [MBytes/s] L3 data volume [GBytes]	0.0007		 4.5	39.1354 787200e-05		
+	ı +		+			+
Metric		Sum		Min	Max	Avg
Runtime (RDTSC) [s] STAT		 0.0036		0.0012	0.0012	0.0012
Runtime unhalted [s] STAT		0.0002		0	0.0002	0.0001
Clock [MHz] STAT		1594.3		795.7124	798.6444	531.4523
CPI STAT		7.03		1.3882	5.6420	2.3434
L3 load bandwidth [MBytes/s] STAT L3 load data volume [GBytes] STAT		510.38 0.00		0 0	474.2809 0.0006	170.1272 0.0002
L3 evict bandwidth [MBytes/s] STAT		134.20		0	131.1663	
L3 evict data volume [GBytes]	0.00		ő	0.0002	0.0001	
L3 bandwidth [MBytes/s] STA	644.58	325	0	605.4471	214.8608	
L3 data volume [GBytes] STA	0.00	007	0	0.0007	0.0002	

Conclusion/Observations

The most useful observations are obtained from the call graph & have already been discussed in it's analysis above. Once we're done optimizing the code, we'll parallelize it using openMP. We should expect significant improvement in the performance of the code since there isn't much dependency in the core algorithm.

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