COL380 Assignment 3

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April 2023

Task 1

Approach

For this assignment, we changed our algorithm from Hybrid to MinTruss [1], which was parallelized with inputs from [2]. The core idea is to modify the MinTruss algorithm by splitting it into phases and using the bulk synchronous parallel model to synchronize across nodes at the end of each bulk phase.

The serial algorithm is as follows:

1. We start off with triangle enumeration, which is done differently from [2]. We instead precompute all the triangles as is done in [3], by ordering the vertices based on their degree and enumerating all incident pairs of edges. This runs in $O\left(\sum \text{outdeg}(v)^2\right)$
2. We then use the same algorithm as MinTruss. However, it's implemented in a different manner, which involves multiple phases of edge deletion. We do this to make it easier to later parallelize the code.

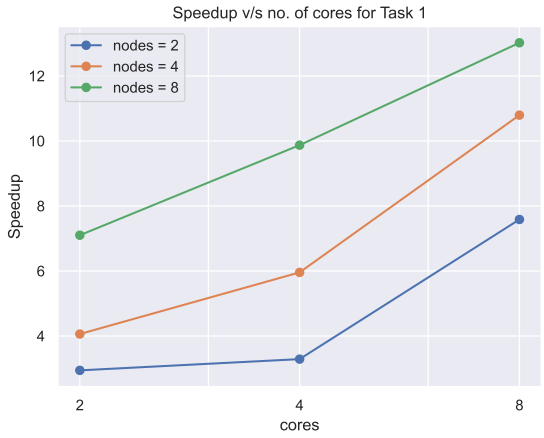
```
1: Compute initial supports and store in sup;
2: k ← 1
3: while |E| > 0 do
4:     F_k ← {e ∈ E : sup(e) < k}
5:     while |F_k| > 0 do
6:         for e ∈ F_k do
7:             for e' ∈ Δ_e do
8:                 sup(e') ← sup(e') − 1
9:             end for
10:            E ← E \{e}
11:            Γ(e) ← k − 1
12:        end for
13:        F_k ← {e ∈ E : sup(e) < k}
14:    end while
15:    k ← k + 1
16: end while
```

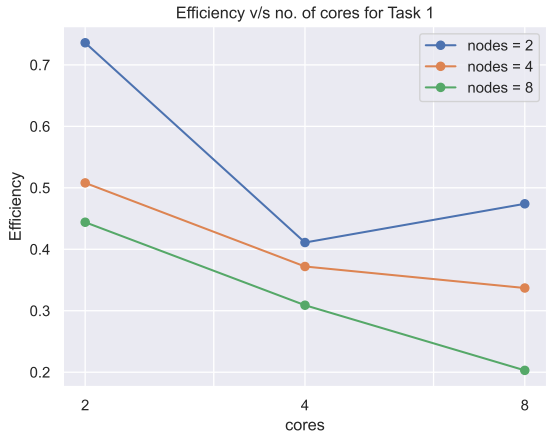
We do not use any atomic operations or mutexes on data in the parallel algorithm. However, synchronization does happen at the end of each phase. Each thread runs lines 6 to 12 concurrently at the end of which the deletions are propagated to each thread. In the parallel version, Every vertex and the edges incident on it are statically owned by a single virtual thread. We have double the

number of virtual threads compared to the number of actual threads for load balancing reasons: this ensures that our algorithm scales irrespective of how unbalanced the initial degree distribution is.

Results

The program was benchmarked on HPC, using the Skylake nodes. The Intel parallel studio 2020 compiler was used as it gave quicker runtimes than GCC, and all runs were done on testcase 10 of assignment 2: this was chosen as it was neither too large nor too small, and gave us results in a short time while still displaying how our program scales to a much larger number of cores.





We notice that:

1. Efficiency decreases with increasing the number of nodes. This is to be expected, as there is more communication over a higher latency network between the nodes compared to shared-memory communication over threads
2. Efficiency also decreases with an increase in the number of threads. This is because of more commmunication between the threads.
3. The speedup is maximum for

nodes	threads	speedup	efficiency	isoefficiency	seq. fraction
2	2	2.943	0.736	14.331	0.119
	4	3.289	0.411	57.191	0.204
	8	7.585	0.474	44.287	0.073
4	2	4.061	0.508	38.727	0.138
	4	5.957	0.372	67.295	0.112
	8	10.795	0.337	78.415	0.063
8	2	7.101	0.444	50.031	0.083
	4	9.872	0.309	89.487	0.072
	8	13.021	0.203	156.303	0.062

Table 1: Statistics for task 1

Isoefficiency is lower-bounded by the overhead, and the overhead is given by $pt(n,p) - t(n,1)$, which is what we've used here to compute isoefficiency. The sequential fraction is computed using the formula

$$f = \frac{\frac{1}{S_p} - \frac{1}{p}}{1 - \frac{1}{p}}$$

The time complexity for our method is roughly given by

$$TC = O\left(\frac{\Delta}{q} + \frac{\sum \deg^{+}(v)^2}{pq}\right)$$

Where Δ is the number of triangles in the graph, q is the number of MPI ranks and p is the number of threads per rank.

Task 2

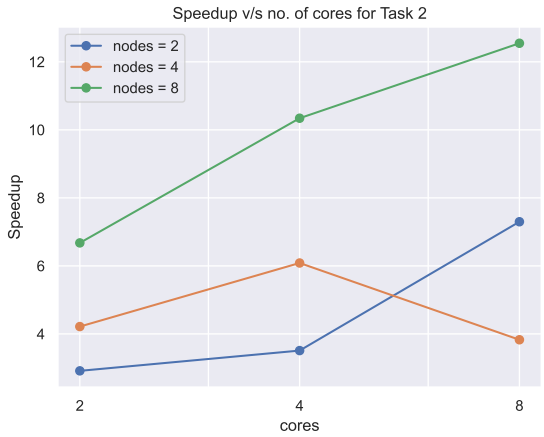
Approach

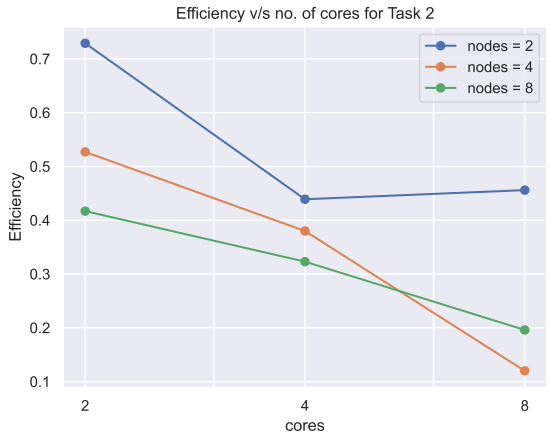
Approach 2 is just an extension of approach 1, which first computes a spanning forest of the k-truss graph on the edges owned by that node. Then we gather all the edges of the spanning forest on node 0, and compute the spanning forest of the entire k-truss graph on node 0. We then broadcast this to all nodes who find the influencers based on this and output to a file in a distributed manner using MPI file IO.

Because of the spanning forest computation on the local nodes, we only need to send $O(n)$ number of edges while gathering the edges at rank 0 instead of $O(m)$ edges.

Results

The evaluation schemes were the same as task 1. The results are given below:





nodes	threads	speedup	efficiency	isoefficiency	seq. fraction
2	2	2.914	0.729	14.871	0.124
	4	3.510	0.439	51.063	0.182
	8	7.298	0.456	47.599	0.079
4	2	4.216	0.527	35.831	0.128
	4	6.085	0.380	65.055	0.108
	8	3.828	0.120	82.575	0.237
8	2	6.676	0.417	55.759	0.093
	4	10.342	0.323	83.599	0.067
	8	12.546	0.196	163.727	0.065

Table 2: Statistics for task 2

The time complexity for this algorithm is

$$TC = O\left(n \log q + \frac{\Delta}{q} + \frac{\sum \deg^+(v)^2}{pq}\right)$$

Where n is the number of nodes in the graph

References

1. Cohen, Jonathan. "Trusses: Cohesive subgraphs for social network analysis." *National security agency technical report 16.3.1 (2008)*.
2. Smith, Shaden, et al. "Truss Decomposition on Shared-Memory Parallel Systems." *2017 IEEE High Performance Extreme Computing Conference (HPEC), IEEE, 2017*, pp. 1–6. DOI.org (Crossref), https://doi.org/10.1109/HPEC.2017.8091049.