

Chapter 11 Massively Parallel Computations

Part II

Theory of Distributed Systems

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Massively Parallel Computation (MPC) Model

– Aims to study parallelism at a more coarse-grained level than classic fine-grained parallel models like PRAM (models settings where communication is much more expensive than computation)

Formal Model

MPC Model

- Input of size N words (1 word = $O(\log N)$ bits, for graphs, $N = O(|E|)$)
- There are $M \ll N$ machines
- Each machine has a memory of S words, i.e., we need $S \ge N/M$
	- We typically assume that $S = N^c$ for a constant $c < 1$
- Time progresses in synchronous rounds, in each round, every machine can send & receive S words to & from other machines
- Initially, the data is partitioned in an arbitrary way among the M machines
	- Such that every machine has a roughly equal part of the data
	- W.l.o.g., data is partitioned in a random way among the machines

Assumption: Input is a graph $G = (V, E)$

- Number of nodes $n = |V|$, number of edges $m = |E|$, nodes have IDs
- Input can be specified by the set E of edges
	- each edge might have some other information, e.g., a weight
	- $-$ for simplicity, assume that every node has degree ≥ 1
- Initially, each edge is given to a uniformly random machine
- We typically assume that $S = \tilde{O}(N/M) = \tilde{O}(m/M)$

Strongly superlinear memory regime

 $S = n^{1+\varepsilon}$ for a constant $\varepsilon > 0$

Strongly sublinear memory regime

 $S = n^{\alpha}$ for a constant $0 < \alpha < 1$

Near-linear memory regime

 $S = n \cdot \text{poly}\log n$

MST in the Near-Linear Memory Regime

- Assume that $S = n \cdot (\log n)^c$ for a sufficiently large constant $c > 0$.
- Instead of MST, we consider a simpler, closely related probem

Connectivity / Component Identification

At the end, algorithm needs to output a number $C(u)$ for each node $u \in V$ such that $C(u) = C(v)$ iff u and v are in the same connected component of G.

Observations

- Algorithm in particular allows to compute whether G is connected
- The MST algorithm from before can be used to solve component identification
	- The algorithm terminates when there are no more edges connecting different fragments. The fragment IDs at the end can be used as outputs
- In combination with some binary search over the edge weights, component identification can be used to also compute an MST
	- Everything we will do can be extended to the MST problem (at the cost of maybe a couple of log-factors in the required memory per machine)

The Single-Round Coordinator Model

We will study the problem in a different communication model

- There is a coordinator and one node for each $v \in V$
- Node ν initially knows the set of its neighbors (i.e., all incident edges)
- Each node $v \in V$ is allowed to send one message to the coordinator
- Afterwards the coordinate needs to be able to compute the output
- We will assume that the nodes have access to shared randomness
- We will use the graph sketching technique

Single Cut Problem:

- Fix $A \subseteq V$. Assume that there are $k \geq 1$ edges across the cut $(A, V \setminus A)$.
- **Goal:** Coordinator needs to return one of the k edges across the cut

Assume first that $k = 1$ **:**

- Define a unique ID for each edge $e = \{u, v\} \in E : ID(e) = ID(u) \circ ID(v)$
- Each node $u \in A$ computes XOR_{u} as

$$
XOR_u := \bigoplus_{e \in E: u \in e} ID(e)
$$

- Each node $u \in V$ sends XOR_{ν} to coordinator
- Coordinator computes

$$
\mathrm{XOR}_A \coloneqq \bigoplus_{u \in A} \mathrm{XOR}_u
$$

Graph Sketching: Warm Up 1

Assume that ! **is an arbitrary value**

Let E_A be the set of edges across the cut $(A, V \setminus A)$ ($|E_A| = k$)

Claim: If we use the same algorithm, $XOR_A = \bigoplus_{e \in E_A} ID(e)$.

Assume that we are given an estimate \widehat{k} s.t. $\frac{\widehat{k}}{2} \leq k \leq \widehat{k}$:

Sample each edge with probability $1/\hat{k}$ and apply alg. with sampled edges

Graph Sketching: Warm Up 2

Assume that $k>1$ and an estimate $\widehat k$ s.t. $\frac{\widehat k}{2}\leq k\leq \widehat k$ is given

- Sample each edge with probability $1/\hat{k}$
- Let E'_A be the sampled edges of E_A (across the cut)

Claim: $\mathbb{P}(|E'_A| = 1) \ge 1/10$.

$$
\mathbb{P}(|E'_A| = 1) = k \cdot \frac{1}{\hat{k}} \cdot \left(1 - \frac{1}{\hat{k}}\right)^{k-1}
$$

$$
\geq \frac{\hat{k}}{2} \cdot \frac{1}{\hat{k}} \cdot \left(1 - \frac{1}{\hat{k}}\right)^{\hat{k}}
$$

$$
\geq \frac{1}{2} \cdot 4^{-\frac{1}{\hat{k}} \cdot \hat{k}}
$$

$$
\geq \frac{1}{10}.
$$

Discussion:

- How can we sample each edge with probability $1/\hat{k}$?
	- Use shared randomness
- If we use the same algorithm, XOR_A is equal to an edge of E_A if $|E'_A| = 1$

How can we distinguish $|E_A'| = 1$ from $|E_A'| \neq 1$?

- We need to make sure that
	- a) The bit-wise XOR of 0 or > 1 edge IDs is not equal to an edge ID
	- b) Edge IDs can be distinguished from the XORs of 0 or > 1 edge IDs

Edge ID of edge $e = \{u, v\} \in E$ (assume $\text{ID}(u) < \text{ID}(v)$) $ID(e) = ID(u) \circ ID(v) \circ R_e$

- R_e is a random bit string of length 80 ln n where each bit is 1 with prob. 1/8
- Let R'_A be the bitwise XOR of R_e for $e \in E'_A$

Claim: Let X be the number of 1s in R'_A . If $|E'_A| = 0$, then $X = 0$, otherwise

- If $|E'_A| = 1$, then $1 < X < 14 \ln n$ with high probability
- If $|E'_A| > 1$, then $X > 14 \ln n$ with high probability

Proof Sketch:

Random Edge IDs

Claim: Let X be the number of 1s in R'_A . If $|E'_A| = 0$, then $X = 0$, otherwise

- If $|E'_A| = 1$, then $1 < X < 14 \ln n$ with high probability
- If $|E'_A| > 1$, then $X > 14 \ln n$ with high probability

Proof Sketch:

• If $|E'_A| \ge 2$, each of the $80 \ln n$ bits of R'_A is 1 with prob. $\ge 2 \cdot \frac{1}{8} \cdot \frac{7}{8}$ 8 $> \frac{1}{5}$ 6

One phase of the Borůvka algorithm

- We need to find one outgoing edge for each fragment
	- Then the coordinator can add a subset of these edges and reduce the number of fragments by a factor 2
- We do not know the number of out-going edges of the different fragments
	- And different fragments might have different numbers
- Use different sampling probabilities: $\frac{1}{n}, \frac{2}{n}, \frac{4}{n}, ..., \frac{1}{2}$ % and send sketches for all probabilities to coordinator
	- For each instance, each $v \in V$ sends XOR of sampled edges to coordinator
- For each fragment, one of the probabilities succeeds with probability $\geq 1/10$
- When having $\Theta(\log n)$ instances for each of the probabilities, we get an outgoing edge for each fragment with high probability
- Each node can send $O(\log^3 n)$ bits to coordinator for one phase

Observation: The protocol does not depend on the fragments

We can therefore send the information for all phases in parallel

Theorem: In the coordinator model, there is a protocol where every node $v \in V$ send $O(\log^4 n)$ bits to the coordinator s.t. the coordinator can solve the connectivity & connected components problem.

Remarks:

- The number of bits can be reduced to $O(\log^3 n)$
	- It is sufficient to succeed with constant prob. for each fragment in each phase
- $\Omega(\log^3 n)$ bits are necessary [Nelson, Yu; 2019]
- Graph sketching has been introduced by [Ahn, Guha, McGregor; 2012]

Implementation in the MPC Model

- 1. For every node $v \in V$, create a responsible machine M_{v}
	- Send each edge $\{u, v\}$ to both M_u and M_v
	- Make sure that each machine gets $\tilde{O}(n)$ edges

- 1. The randomness for each edge can be generated initially by the machine that holds the edge
	- Also send the randomness for the edge $\{u, v\}$ to M_u and M_v

2. Use one additional machine for the coordinator

Theorem: In the MPC model with $S = \tilde{O}(n)$, the connectivity & connected components problem can be solve in $O(1)$ rounds.

Discussion

- Graph sketching can help in many different contexts, e.g.,
	- also in the strongly-sublinear memory regime to save communication
	- in the streaming model
	- in the standard distributed model to save message
- In the strongly sublinear memory regime, it is not known whether it is possible to be faster than $O(\log n)$ rounds
	- It is widely believed that there should be an $\Omega(\log n)$ lower bound
	- Even the following simple version of the problem seems to require $\Omega(\log n)$ time

distinguish 2 cycles of length $n/2$ from one cycle of length n