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ON DYNAMIC BREADTH-FIRST SEARCH IN EXTERNAL-MEMORY

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ABSTRACT. We provide the first non-trivial result on dynamic breadth-first search (BFS) in external-memory: For general sparse undirected graphs of initially n nodes and $O(n)$ edges and monotone update sequences of either $\Theta(n)$ edge insertions or $\Theta(n)$ edge deletions, we prove an amortized high-probability bound of $O(n/B^{2/3} + \text{sort}(n) \cdot \log B)$ I/Os per update. In contrast, the currently best approach for static BFS on sparse undirected graphs requires $\Omega(n/B^{1/2} + \text{sort}(n))$ I/Os.

1. Introduction

Breadth first search (BFS) is a fundamental graph traversal strategy. It can also be viewed as computing single source shortest paths on unweighted graphs. It decomposes the input graph $G = (V, E)$ of n nodes and m edges into at most n levels where level i comprises all nodes that can be reached from a designated source s via a path of i edges, but cannot be reached using less than i edges.

The objective of a dynamic graph algorithm is to efficiently process an online sequence of update and query operations; see [8, 14] for overviews of classic and recent results. In our case we consider BFS under a sequence of either $\Theta(n)$ edge insertions, but not deletions (*incremental* version) or $\Theta(n)$ edge deletions, but not insertions (*decremental* version). After each edge insertion/deletion the updated BFS level decomposition has to be output.

1.1. Computation models.

We consider the commonly accepted external-memory (EM) model of Aggarwal and Vitter [1]. It assumes a two level memory hierarchy with faster internal memory having a capacity to store M vertices/edges. In an I/O operation, one block of data, which can store B vertices/edges, is transferred between disk and internal memory. The measure of performance of an algorithm is the number of I/Os it performs. The number of I/Os needed to read N contiguous items from disk is $\text{scan}(N) = \Theta(N/B)$. The number of I/Os required

to sort N items is $\text{sort}(N) = \Theta((N/B)\log_{M/B}(N/B))$. For all realistic values of N, B, and M, $\text{scan}(N) < \text{sort}(N) \ll N$.

There has been a significant number of publications on external-memory graph algorithms; see [12, 16] for recent overviews. However, we are not aware of any dynamic graph algorithm in the fully external-memory case (where $|V| > M$).

1.2. Results.

We provide the first non-trivial result on dynamic BFS in external-memory. For general sparse undirected graphs of initially n nodes and $O(n)$ edges and either $\Theta(n)$ edge insertions or $\Theta(n)$ edge deletions, we prove an amortized high-probability bound of $O(n/B^{2/3}+\text{sort}(n)\cdot \log B)$ I/Os per update. In contrast, the currently best bound for static BFS on sparse undirected graphs is $O(n/B^{1/2} + \text{sort}(n))$ I/Os [11].

Also note that for general sparse graphs and worst-case monotone sequences of $\Theta(n)$ updates in *internal-memory* there is asymptotically no better solution than performing $\Theta(n)$ runs of the linear-time static BFS algorithm, even if after each update we are just required to report the changes in the BFS tree (see Fig. 1 for an example). In case $\Omega(n/B^{1/2}+\text{sort}(n))$ I/Os should prove to be a lower bound for static BFS in external-memory, then our result yields an interesting differentiator between static vs. dynamic BFS in internal and external memory.
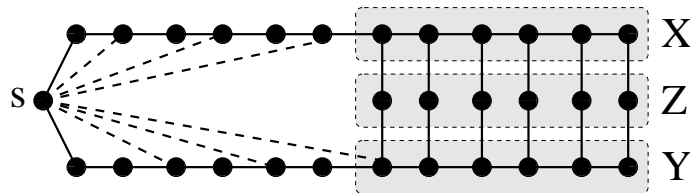

Figure 1: Example for a graph class where each update requires $\Omega(n)$ changes in the BFS tree: inserting new (dashed) edges alternatingly shortcut the distances from s to **X** and s to **Y**. As a result, in the updated BFS tree the parents of all vertices in **Z** keep on changing between **X** and **Y**.

1.3. Organization of the paper.

In Section 2 we will review known BFS algorithms for static undirected graphs. Then we consider traditional and new external-memory methods for graph clustering (Section 3). Subsequently, in Section 4 we provide the new algorithm and analyze it in Section 5. Final remarks concerning extensions and open problems are given in Sections 6 and 7, respectively.

2. Review of Static BFS Algorithms

Internal-Memory. BFS is well-understood in the RAM model. There exists a simple linear time algorithm [6] (hereafter referred as IM_BFS) for the BFS traversal in a graph. IM_BFS keeps a set of appropriate candidate nodes for the next vertex to be visited in a FIFO queue Q. Furthermore, in order to find out the unvisited neighbors of a node from its adjacency list, it marks the nodes as either visited or unvisited.

Unfortunately, as the storage requirements of the graph starts approaching the size of the internal memory, the running time of this algorithm deviates significantly from the predicted $O(n + m)$ asymptotic performance of the RAM model: checking whether edges lead to already visited nodes altogether needs $\Theta(m)$ I/Os in the worst case; unstructured indexed access to adjacency lists may add another $\Theta(n + m/B)$ I/Os.

EM-BFS for dense undirected graphs. The algorithm by Munagala and Ranade [13] (referred as MR_BFS) ignores the second problem but addresses the first by exploiting the fact that the neighbors of a node in BFS level $t - 1$ are all in BFS levels $t - 2$, $t - 1$ or t. Let $L(t)$ denote the set of nodes in BFS level t, and let $A(t)$ be the multi-set of neighbors of nodes in $L(t-1)$. Given $L(t-1)$ and $L(t-2)$, MR_BFS builds $L(t)$ as follows: Firstly, $A(t)$ is created by $|L(t-1)|$ random accesses to get hold of the adjacency lists of all nodes in $L(t-1)$. Thereafter, duplicates are removed from $A(t)$ to get a sorted set $A'(t)$. This is done by sorting $A(t)$ according to node indices, followed by a scan and compaction phase. The set $L(t) := A'(t) \setminus \{L(t-1) \cup L(t-2)\}$ is computed by scanning "in parallel" the sorted sets of $A'(t), L(t-1)$, and $L(t-2)$ to filter out the nodes already present in $L(t-1)$ or $L(t-2)$. The resulting worst-case I/O-bound is $O\left(\sum_t L(t) + \sum_t \text{sort}(A(t))\right) = O\left(n + \text{sort}(n + m)\right)$. The algorithm outputs a BFS-level decomposition of the vertices, which can be easily transformed into a BFS tree using $O(\text{sort}(n + m))$ I/Os [4].

EM-BFS for sparse undirected graphs. Mehlhorn and Meyer suggested another approach [11] (MM_BFS) which involves a preprocessing phase to restructure the adjacency lists of the graph representation. It groups the vertices of the input graph into disjoint clusters of small diameter in G and stores the adjacency lists of the nodes in a cluster contiguously on the disk. Thereafter, an appropriately modified version of MR_BFS is run. MM_BFS exploits the fact that whenever the first node of a cluster is visited then the remaining nodes of this cluster will be reached soon after. By spending only one random access (and possibly, some sequential accesses depending on cluster size) to load the whole cluster and then keeping the cluster data in some efficiently accessible data structure (pool) until it is all processed, on sparse graphs the total amount of I/Os can be reduced by a factor of up to $\sqrt{B}$: the neighboring nodes of a BFS level can be computed simply by scanning the pool and not the whole graph. Though some edges may be scanned more often in the pool, unstructured I/Os to fetch adjacency lists is considerably reduced, thereby reducing the total number of I/Os.

3. Preprocessing

3.1. Traditional preprocessing within MM_BFS.

Mehlhorn and Meyer [11] proposed the algorithms MM_BFS_R and MM_BFS_D, out of which the first is randomized and the second is deterministic. In MM_BFS_R, the partitioning is generated "in parallel rounds": after choosing master nodes independently and uniformly at random, in each round, each master node tries to capture all unvisited neighbors of its current sub-graph into its partition, with ties being resolved arbitrarily.

A similar kind of randomized preprocessing is also applied in parallel [15] and streaming [7] settings. There, however, a dense compressed graph among the master nodes is produced, causing rather high parallel work or large total streaming volume, respectively.

The MM_BFS_D variant first builds a spanning tree T_s for the connected component of G that contains the source node. Arge et al. [2] show an upper bound of $O((1 + \log\log(B \cdot n/m)) \cdot \text{sort}(n + m))$ I/Os for computing such a spanning tree. Each undirected edge of T_s is then replaced by two oppositely directed edges. Note that a bi-directed tree always has at least one Euler tour. In order to construct the Euler tour around this bi-directed tree, each node chooses a cyclic order [3] of its neighbors. The successor of an incoming edge is defined to be the outgoing edge to the next node in the cyclic order. The tour is then broken at the source node and the elements of the resulting list are then stored in consecutive order using an external memory list-ranking algorithm; Chiang et al. [5] showed how to do this in sorting complexity. Thereafter, we chop the Euler tour into *chunks* of $\max\{1, \sqrt{\frac{n \cdot B}{n+m}}\}$ nodes and remove duplicates such that each node only remains in the first chunk it originally occurs; again this requires a couple of sorting steps. The adjacency lists are then re-ordered based on the position of their corresponding nodes in the chopped duplicate-free Euler tour: all adjacency lists for nodes in the same chunks form a cluster and the distance in G between any two vertices whose adjacency-lists belong to the same cluster is bounded by $\max\{1, \sqrt{\frac{n \cdot B}{n+m}}\}$.

3.2. Modified preprocessing for dynamic BFS.

The preprocessing methods for the static BFS in [11] may produce very unbalanced clusters: for example, with MM_BFS_D using chunk size $1 < \mu < O(\sqrt{B})$ there may be $\Omega(n/\mu)$ clusters being in charge of only $O(1)$ adjacency-lists each. For the dynamic version, however, we would like to argue that each random access to a cluster not visited so far provides us with $\Omega(\mu)$ new adjacency-lists. Unfortunately, finding such a clustering I/O-efficiently seems to be quite hard. Therefore, we shall already be satisfied with an Euler tour based randomized construction ensuring that the *expected* number of adjacency-lists kept in all but one[1] clusters is $\Omega(\mu)$.

The preprocessing from MM_BFS_D is modified as follows: each vertex v in the spanning tree T_s is assigned an independent binary random number $r(v)$ with $\mathbf{P}[r(v) = 0] = \mathbf{P}[r(v) = 1] = 1/2$. When removing duplicates from the Euler tour, instead of storing v's adjacency-list in the cluster related to the chunk with the *first* occurrence of a vertex v, now we only stick to its first occurrence iff $r(v) = 0$ and otherwise ($r(v) = 1$) store v's adjacency-list in the cluster that corresponds to the *last* chunk of the Euler tour v appears in. For leaf nodes v, there is only one occurrence on the tour, hence the value of $r(v)$ is irrelevant. Obviously, each adjacency-lists is stored only once. Furthermore, the modified procedure maintains all good properties of the standard preprocessing within MM_BFS_D like guaranteed bounded distances of $O(\mu)$ in G between the vertices belonging to the same cluster and $O(n/\mu)$ clusters overall.

Lemma 3.1. *For chunk size $\mu > 1$ and each but the last chunk, the expected number of adjacency-lists kept is at least $\mu/8$.*

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[1]The last chunk of the Euler tour only visits $((2 \cdot n' - 1) \bmod \mu) + 1$ vertices where n' denotes the number of vertices in the connected component of the starting node s.

Proof. Let $R = (v_1, \ldots, v_\mu)$ be the sequence of vertices visited by an arbitrary chunk $\mathcal{R}$ of the Euler tour $\mathcal{T}$, excluding the last chunk. Let a be the number of entries in R that represent first or last visits of inner-tree vertices from the spanning tree T_s on $\mathcal{T}$. These a entries account for an expected number of $a/2$ adjacency-lists actually stored and kept in $\mathcal{R}$. Note that if for some vertex $v \in \mathcal{T}$ both its first and last visit happen within $\mathcal{R}$, then v's adjacency-list is kept with probability one. Similarly, if there are any visits of leaf nodes from T_s within $\mathcal{R}$, then their adjacency-lists are kept for sure; let b denote the number of these leaf node entries in R. What remains are $\mu - a - b$ *intermediate* (neither first nor last) visits of vertices within $\mathcal{R}$; they do not contribute any additional adjacency-lists.

We can bound $\mu - a - b$ using the observation that any intermediate visit of a tree node v on $\mathcal{T}$ is preceded by a last visit of a child v' of v and proceeded by a first visit of another child v'' of v. Thus, $\mu - a - b \leq \lceil \mu/2 \rceil$, that is $a + b \geq \lfloor \mu/2 \rfloor$, which implies that the expected number of distinct adjacency-lists being kept for $\mathcal{R}$ is at least $\lfloor \mu/2 \rfloor / 2 \geq \mu/8$. ∎

4. The Dynamic Incremental Algorithm

In this section we concentrate on the incremental version for sparse graphs with $\Theta(n)$ updates where each update inserts an edge. Thus, BFS levels can only decrease over time. Before we start, let us fix some notation: for $i \geq 1$, $G_i = (V, E_i)$ is to denote the graph after the i-th update, G_0 is the initial graph. Let $d_i(v)$, $i \geq 0$, stand for the BFS level of node v if it can be reached from the source node s in G_i and n otherwise. Furthermore, for $i \geq 1$, let $\Delta d_i(v) = |d_{i-1}(v) - d_i(v)|$. The main ideas of our approach are as follows:

Checking Connectivity; Type A updates. In order to compute the BFS levels for G_i, $i \geq 1$, we first run an EM connected components algorithm (for example the one in [13] taking $O(\text{sort}(n) \cdot \log B)$ I/Os) in order to check, whether the insertion of the i-th edge (u, v) enlarges the connected component $\mathcal{C}_s$ of the source vertex s. If yes (let us call this a *Type A update*), then w.l.o.g. let $u \in \mathcal{C}_s$ and let $\mathcal{C}_v$ be the connected component that comprises v. The new edge (u, v) is then the only connection between the existing BFS-tree for s and $\mathcal{C}_v$. Therefore, we can simply run MR_BFS on the subgraph G' defined by the vertices in $\mathcal{C}_v$ with source v and add $d_{i-1}(u) + 1$ to all distances obtained. This takes $O(n_v + \text{sort}(n))$ I/Os where n_v denotes the number of vertices in $\mathcal{C}_v$.

If the i-th update does not merge $\mathcal{C}_s$ with some other connected component but adds an edge within $\mathcal{C}_s$ (*Type B update*) then we need to do something more fancy:

Dealing with small changes; Type B updates. Now for computing the BFS levels for G_i, $i \geq 1$, we pre-feed the adjacency-lists into a sorted pool $\mathcal{H}$ according to the BFS levels of their respective vertices in G_{i-1} using a certain advance $\alpha > 1$, i.e., the adjacency list for v is added to $\mathcal{H}$ when creating BFS level $\max\{0, d_{i-1}(v) - \alpha\}$ of G_i. This can be done I/O-efficiently as follows. First we extract the adjacency-lists for vertices having BFS levels up to α in G_{i-1} and put them to $\mathcal{H}$ where they are kept sorted by node indices. From the remaining adjacency-lists we build a sequence $\mathcal{S}$ by sorting them according to BFS levels in G_{i-1} (primary criterion) and node indices (secondary criterion). For the construction of each new BFS level of G_i we merge a subsequence of $\mathcal{S}$ accounting for one BFS level in G_{i-1} with $\mathcal{H}$ using simple scanning.

Therefore, if $\Delta d_i(v) \leq \alpha$ for all $v \in V$ then all adjacency-lists will be added to $\mathcal{H}$ in time and can be consumed from there without random I/O. Each adjacency-list is scanned

at most once in $\mathcal{S}$ and at most α times in $\mathcal{H}$. Thus, if $\alpha = o(\sqrt{B})$ this approach causes less I/O than MM_BFS.

Dealing with larger changes. Unfortunately, in general, there may be vertices v with $\Delta d_i(v) > \alpha$. Their adjacency-lists are not prefetched into $\mathcal{H}$ early enough and therefore have to be imported into $\mathcal{H}$ using random I/Os to whole clusters just like it is done in MM_BFS. However, we apply the modified clustering procedure described in Section 3.2 on G_{i-1}, the graph without the i-th new edge (whose connectivity is the same as that of G_i) with chunk size $\alpha/4$.

Note that this may result in $\Theta(n/\alpha)$ cluster accesses, which would be prohibitive for small α. Therefore we restrict the number of random cluster accesses to $\alpha \cdot n/B$. If the dynamic algorithm does not succeed within these bounds then it increases α by a factor of two, computes a new clustering for G_{i-1} with larger chunk size and starts a *new attempt* by repeating the whole approach with the increased parameters. Note that we do not need to recompute the spanning tree for the for the second, third, ... attempt.

At most $O(\log B)$ attempts per update. The j-th attempt, $j \geq 1$, of the dynamic approach to produce the new BFS-level decomposition will apply an advance of $\alpha_j := 32 \cdot 2^j$ and recompute the modified clustering for G_{i-1} using chunk size $\mu_j := 8 \cdot 2^j$. Note that there can be at most $O(\log \sqrt{B}) = O(\log B)$ failing attempts for each edge update since by then our approach allows sufficiently many random accesses to clusters so that all of them can be loaded explicitly resulting in an I/O-bound comparable to that of static MM_BFS. In Section 5, however, we will argue that for most edge updates within a longer sequence, the advance value and the chunk size value for the succeeding attempt are bounded by $O(B^{1/3})$ implying significantly improved I/O performance.

Restricting waiting time in $\mathcal{H}$. There is one more important detail to take care of: when adjacency-lists are brought into $\mathcal{H}$ via explicit cluster accesses (because of insufficient advance α_j in the prefetching), these adjacency-lists will re-enter $\mathcal{H}$ once more later on during the (for these adjacency-lists by then useless) prefetching. Thus, in order to make sure that unnecessary adjacency-lists do not stay in $\mathcal{H}$ forever, each entry in $\mathcal{H}$ carries a time-stamp ensuring that superfluous adjacency-lists are evicted from $\mathcal{H}$ after at most $\alpha_j = O(2^j)$ BFS levels.

Lemma 4.1. *For sparse graphs with $O(n)$ updates, each Type B update succeeding during the j-th attempt requires $O(2^j \cdot n/B + \mathrm{sort}(n) \cdot \log B)$ I/Os.*

Proof. Deciding whether a Type B update takes place essentially requires a connected components computation, which accounts for $O(\mathrm{sort}(n) \cdot \log B)$ I/Os. Within this I/O bound we can also compute a spanning tree T_s of the component holding the starting vertex s but excluding the new edge. Subsequently, there are $j = O(\log B)$ attempts, each of which uses $O(\mathrm{sort}(n))$ I/Os to derive a new modified clustering based on an Euler tour with increasing chunk sizes around T_s. Furthermore, before each attempt we need to initialize $\mathcal{H}$ and $\mathcal{S}$, which takes $O(\mathrm{sort}(n))$ I/Os per attempt. The worst-case number of I/Os to (re-) scan adjacency-lists in $\mathcal{H}$ or to explicitly fetch clusters of adjacency-lists doubles after each attempt. Therefore it asymptotically suffices to consider the (successful) last attempt j, which causes $O(2^j \cdot n/B)$ I/Os. Furthermore, each attempt requires another $O(\mathrm{sort}(n))$ I/Os to pre-sort explicitly loaded clusters before they can be merged with $\mathcal{H}$ using a single scan just like in MM_BFS. Adding all contributions yields the claimed I/O bound of $O(2^j \cdot n/B + \mathrm{sort}(n) \cdot \log B)$ for sparse graphs.   ■

5. Analysis

We split our analysis of the incremental BFS algorithm into two parts. The first (and easy one) takes care of Type A updates:

Lemma 5.1. *For sparse undirected graphs with $\Theta(n)$ updates, there are at most $n-1$ Type A updates causing $O(n \cdot \mathrm{sort}(n) \cdot \log B)$ I/Os in total.*

Proof. Each Type A update starts with an EM connected components computation causing $O(\mathrm{sort}(n) \cdot \log B)$ I/Os per update. Since each node can be added to the connected component $\mathcal{C}_s$ holding the starting vertex s only once, the total number of I/Os spend in calls to the MR-BFS algorithm on components to be merged with $\mathcal{C}_s$ is $O(n + \mathrm{sort}(n))$. Producing the output takes another $O(\mathrm{sort}(n))$ per update. ∎

Now we turn to Type B updates:

Lemma 5.2. *For sparse undirected graphs with $\Theta(n)$ updates, all Type B updates cause $O(n \cdot (n^{2/3} + \mathrm{sort}(n) \cdot \log B))$ I/Os in total with high probability.*

Proof. Recall that $d_i(v)$, $i \geq 0$, stands for the BFS level of node v if it can be reached from the source node s in G_i and n otherwise. If upon the i-th update the dynamic algorithm issues an explicit fetch for the adjacency-lists of some vertex v kept in some cluster C then this is because $\Delta d_i(v) = d_{i-1}(v) - d_i(v) > \alpha$ for the current advance α. Note that for all other vertices $v' \in C$, there is a path of length at most μ in G_{i-1}, implying that $|d_{i-1}(v') - d_{i-1}(v)| \leq \mu$ as well as $|d_i(v) - d_i(v')| \leq \mu$. Having current chunk size $\mu = \alpha/4$, this implies

$$
\begin{aligned}
\Delta d_i(v') &= d_{i-1}(v') - d_i(v') \\
&= d_{i-1}(v') - d_{i-1}(v) + d_{i-1}(v) - d_i(v) + d_i(v) - d_i(v') \\
&> \alpha - 2\mu \\
&\geq \alpha/2.
\end{aligned}
$$

If the i-th update needs j attempts to succeed then, during the (failing) attempt $j - 1$, it has tried to explicitly access $\alpha_{j-1} \cdot n/B + 1$ distinct clusters. Out of these at least $\alpha_{j-1} \cdot n/B = 2^{j+4} \cdot n/B$ clusters carry an expected amount of at least $\mu_{j-1}/8 = 2^{j-1}$ adjacency-lists each. This accounts for an expected number of at least $2^{2 \cdot j+3} \cdot n/B$ distinct vertices, each of them featuring $\Delta d_i(\cdot) \geq \alpha_{j-1}/2 = 2^{j+3}$. With probability at least $1/2$ we actually get at least half of the expected amount of distinct vertices/adjacency-lists, i.e., $2^{2 \cdot j+2} \cdot n/B$. Therefore, using the definitions $D_i = \sum_{v \in V \setminus \{s\}} d_i(v)$ and $\Delta D_i = |D_{i-1} - D_i|$, if the i-th update succeeds within the j-th attempt we have $\Delta D_i \geq 2^{3 \cdot j+5} \cdot n/B =: Y_j$ with probability at least $1/2$. Let us call this event *a large j-yield*.

Since each attempt uses a new clustering with independent choices for $r(\cdot)$, if we consider two updates i' and i'' that succeed after the same number of attempts j, then both i' and i'' have a large yield with probability at least $1/2$, independent of each other. Therefore, we can use Chernoff bounds [10] in order to show that out of $k \geq 16 \cdot c \cdot \ln n$ updates that all succeed within their j-th attempt, at least $k/4$ of them have a large j-yield with probability at least $1 - n^{-c}$ for an arbitrary positive constant c. Subsequently we will prove an upper bound on the total number of large j-yields that can occur during the whole update sequence.

The quantity ΔD_i provides a global measure as for how much the BFS levels change after inclusion of the i-th edge from the update sequence. If there are $m' = \Theta(n)$ edge inserts in total, then

$$n^2 > D_0 \geq D_1 \geq \ldots \geq D_{m'-1} \geq D_{m'} > 0.$$

A large j-yield means $\Delta D_i \geq Y_j$. Therefore, in the worst case there are at most $n^2/Y_j = n^2/(2^{3 \cdot j+5} \cdot n/B) = n \cdot B/2^{3 \cdot j+5}$ large j-yield updates and – according to our discussion above – it needs at most $k_j := 4 \cdot n \cdot B/2^{3 \cdot j+5}$ updates that succeed within the j-th attempt to have at least $k_j/4$ large j-yield updates with high probability[2].

For the last step of our analysis we will distinguish two kinds of Type B updates: those that finish using an advance value $\alpha_{j*} < B^{1/3}$ (Type B1), and the others (Type B2). Independent of the subtype, an update costs $O(\alpha_{j*} \cdot n/B + \text{sort}(n) \cdot \log B) = O(2^{j^*} \cdot n/B + \text{sort}(n) \cdot \log B)$ I/Os by Lemma 4.1. Obviously, for an update sequence of $m' = \Theta(n)$ edge insertions there can be at most $\Theta(n)$ updates of Type B1, each of them accounting for at most $O(n/B^{2/3} + \text{sort}(n) \cdot \log B)$ I/Os. As for Type B2 updates we have already shown that with high probability there are at most $O(n \cdot B/2^{3 \cdot j^*})$ updates that succeed with advance value $\Theta(2^{j^*})$. Therefore, using Boole's inequality, the total amount of I/Os for all Type B2 updates is bounded by

$$O\left(\left(\sum_{g \geq 0} \frac{n \cdot B}{(B^{1/3} \cdot 2^g)^3} \cdot \frac{B^{1/3} \cdot 2^g \cdot n}{B}\right) + n \cdot \text{sort}(n) \cdot \log B\right) =$$

$O(n \cdot (n/B^{2/3} + \text{sort}(n) \cdot \log B))$ with high probability.   ∎

Combining the two lemmas of this section implies

Theorem 5.3. *For general sparse undirected graphs of initially n nodes and $O(n)$ edges and $\Theta(n)$ edge insertions, dynamic BFS can be solved using amortized $O(n/B^{2/3} + \text{sort}(n) \cdot \log B)$ I/Os per update with high probability.*

6. Decremental Version and Extensions.

Having gone through the ideas of the incremental version, it is now close to trivial to come up with a symmetric external-memory dynamic BFS algorithm for a sequence of edge deletions: instead of pre-feeding adjacency-lists into using an *advance* of α_j levels, we now apply a *lag* of α_j levels. Therefore, the adjacency-list for a vertex v is found in $\mathcal{H}$ as long as the deletion of the i-th edge does not increase $d_i(v)$ by more than α. Otherwise, an explicit random access to the cluster containing v's adjacency-list is issued later on. All previously used amortization arguments and bounds carry through, the only difference being that $d_i(\cdot)$ values may monotonically increase instead of decrease.

Better amortized bounds can be obtained if $\omega(n)$ updates take place and/or G_0 has $\omega(n)$ edges. Then we have the potential to amortize more random accesses per attempt, which leads to larger j-yields and reduces the worst-case number of expensive updates. Consequently, we can reduce the defining threshold between Type B1 and Type B2 updates,

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[2]We also need to verify that $k_j \geq 16 \cdot c \cdot \ln n$. As observed before, the dynamic algorithm will not increase its advance and chunk size values beyond $O(\sqrt{B})$ implying $2^j = O(\sqrt{B})$. But then we have $k_j = 4 \cdot n \cdot B/2^{3 \cdot j+5} = \Omega(n/\sqrt{B})$ and $n/\sqrt{B} \geq n/\sqrt{M} \geq n/\sqrt{n} \geq 16 \cdot c \cdot \ln n$ for sufficiently large n.

thus eventually yielding better amortized I/O bounds. Details we be provided in the full version of this paper.

Modifications along similar lines are in order if external-memory is realized by flash disks [9]: compared to hard disks, flash memory can sustain many more unstructured read I/Os per second but on the other hand flash memory usually offers less read/write bandwidth than hard disks. Hence, in algorithms like ours that are based on a trade-off between unstructured read I/Os and bulk read/write I/Os, performance can be improved by allowing more unstructured read I/Os (fetching clusters) if this leads to less overall I/O volume (scanning hot pool entries).

7. Conclusions

We have given the first non-trivial external-memory algorithm for dynamic BFS. Even though we obtain significantly better I/O bounds than for the currently best static algorithm, there are a number of open problems: first of all, our bounds dramatically deteriorate for mixed update sequences (edge insertions and edge deletions in arbitrary order and proportions); besides oscillation effects, a single edge deletion (insertion) may spoil a whole chain of amortizations for previous insertions (deletions). Also, it would be interesting to see, whether our bounds can be further improved or also hold for shorter update sequences. Finally, it would be nice to come up with a deterministic version of the modified clustering.

Acknowledgements

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