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IMPROVED BOUNDS FOR FINGER SEARCH ON A RAM

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Abstract

We present a new finger search tree with $O(1)$ worst-case update time and $O(\log\log d)$ expected search time with high probability in the Random Access Machine (RAM) model of computation for a large class of input distributions. The parameter d represents the number of elements (distance) between the search element and an element pointed to by a finger, in a finger search tree that stores n elements. Our data structure improves upon a previous result by Andersson and Mattson that exhibits expected $O(\log\log n)$ time and $O(1)$ worst-case update time, by incorporating the distance d into the search time complexity, thus removing the dependence on n, and by proving that the attained search time complexity holds with high probability. For the need of the analysis we model the updates by a "balls and bins" combinatorial game that is interesting in its own right as it involves insertions and deletions of balls according to an unknown distribution.

1 Introduction

Search trees and in particular finger search trees are fundamental data structures that have been extensively studied and used. For example, finger search trees lead to optimal algorithms for the basic operations of union, intersection and difference on sets [18], allow for efficient list splitting [18] and efficient implementation of priority queues [12], are used to efficiently sort nearly ordered files [12] and to sort Jordan sequences in linear time [14]. They also find applications in computational geometry, for example in constructing the visibility graph of a polygon [13, 11], in deriving optimal algorithms for the 3-dimensional layers-of-maxima problem [3], and in obtaining improved methods for dynamic point location [3].

A *finger search tree* is a leaf-oriented search tree storing n elements, in which the search procedure can start from an arbitrary element pointed to by a *finger* f (for simplicity, we shall not distinguish throughout the paper between f and the element pointed to by f). The goal is: (i) to find another element x stored in the tree in a time complexity that is a function of the "distance" (number of leaves) d between f and x; and (ii) to update the data structure after the deletion of f or after the insertion of a new element next to f. Several results for finger search trees have

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been achieved on the Pointer Machine (PM) and the Random Access Machine (RAM) models of computation.

In the RAM model, finger search trees with $O(1)$ update time and $O(\log d)$ search time have already been devised by Dietz and Raman [7]. Recently, Andersson and Thorup [2] presented a new data structure for finger search trees with $O(1)$ update time and $O(\sqrt{\log d/\log\log d})$ search time, which is optimal since there exists a matching lower bound for searching on a RAM. In the PM model, Brodal et al. [4] presented very recently a finger search tree with $O(1)$ update time and $O(\log d)$ search time, which is optimal for this model. All these bounds are worst-case time complexities and since they have matching lower bounds, there is no room for improvement.

However, simpler data structures and/or improvements regarding the search complexities can be obtained if randomization is allowed, or if certain classes of input distributions are considered. An example for the former is the simple and elegant finger search tree developed by Seidel and Aragon [23] that achieves $O(1)$ expected update time when decisions for rebalancing operations are guided by tosses of coins, while the search operation is carried out in $O(\log d)$ expected time. A notorious example for the latter is the method of *interpolation search*, first suggested by Peterson [22], which for random data generated according to the *uniform* distribution achieves $\Theta(\log\log n)$ expected search time. This was shown in [10, 21, 27]. Willard in [25] showed that this time bound holds for an extended class of distributions, called *regular*[1].

A natural extension is to adapt interpolation search into dynamic data structures, that is, data structures which support insertion and deletion of elements in addition to interpolation search. Their study was started with the works of [9, 15] for insertions and deletions performed according to the uniform distribution, and continued by Mehlhorn and Tsakalidis [19], and Andersson and Mattsson [1] for *μ-random* insertions and *random* deletions, where μ is a so-called *smooth* density. An insertion is μ-random if the key to be inserted is drawn randomly with density function μ; a deletion is random if every key present in the data structure is equally likely to be deleted (these notions of randomness are also described in [16]).

The notion of *smooth* input distributions that determine insertions of elements in the update sequence were introduced in [19], and were further generalized and refined in [1]. Given two functions f_1 and f_2, a density function $\mu = \mu[a,b](x)$ is *(f_1, f_2)-smooth* [1] if there exists a constant β, such that for all c_1, c_2, c_3, $a \le c_1 < c_2 < c_3 \le b$, and all integers n, it holds that

$$\int_{c_2 - \frac{c_3 - c_1}{f_1(n)}}^{c_2} \mu[c_1, c_3](x)dx \le \frac{\beta \cdot f_2(n)}{n}$$

where $\mu[c_1, c_3](x) = 0$ for $x < c_1$ or $x > c_3$, and $\mu[c_1, c_3](x) = \mu(x)/p$ for $c_1 \le x \le c_3$ where $p = \int_{c_1}^{c_3} \mu(x)dx$. The class of smooth distributions is a superset of both regular and uniform classes.

In [19] a dynamic interpolation search data structure was introduced, called *Interpolation Search Tree (IST)*. This data structure requires $O(n)$ space for storing n elements. The amortized insertion and deletion cost is $O(\log n)$, while the expected amortized insertion and deletion cost is $O(\log\log n)$. The worst case search time is $O(\log^2 n)$, while the expected search time is $O(\log\log n)$ on sets generated by μ-random insertions and random deletions, where μ is a $(\lceil n^a \rceil, \sqrt{n})$-smooth density function and $\frac{1}{2} \le a < 1$. An IST is a multi-way tree, where the degree of a node u depends on the number of leaves of the subtree rooted at u (in the ideal case the degree of u is the square root of this number). Each node of the tree is associated with two arrays: a REP array which stores a set of sample elements, one element from each subtree, and an ID array that stores a set

[1] A density μ is regular if there are constants b_1, b_2, b_3, b_4 such that $\mu(x) = 0$ for $x < b_1$ or $x > b_2$, and $\mu(x) \ge b_3 > 0$ and $|\mu'(x)| \le b_4$ for $b_1 \le x \le b_2$.

of sample elements approximating the inverse distribution function. In particular, for a node with degree $\sqrt{m}$ and having m leaves in its subtree, the ID array divides the interval covered by the node in m^a subintervals, where $1/2 \leq a < 1$. Each interval is associated with a pointer to a proper subtree. The search algorithm for the IST uses the ID array in each visited node to interpolate REP and locate the element, and consequently the subtree where the search is to be continued.

In [1], Andersson and Mattsson explored further the idea of dynamic interpolation search by observing that: (i) the larger the ID array the bigger becomes the class of input distributions that can be efficiently handled with an IST-like construction; and (ii) the IST update algorithms may be simplified by the use of a static, implicit search tree whose leaves are associated with binary search trees and by applying the incremental global rebuilding technique of [20]. The resulting new data structure in [1] is called the *Augmented Sampled Forest (ASF)*. Assuming that $H(n)$ is an increasing function denoting the height of the static implicit tree, Andersson and Mattsson [1] showed that an expected search and update time of $\Theta(H(n))$ can be achieved for μ-random insertions and random deletions where μ is $(n \cdot g(H(n)), H^{-1}(H(n)-1))$-smooth and g is a function satisfying $\sum_{i=1}^{\infty} g(i) = \Theta(1)$. In particular, for $H(n) = \Theta(\log\log n)$ and $g(x) = x^{-(1+\varepsilon)}$ ($\varepsilon > 0$), they get $\Theta(\log\log n)$ expected search and update time for any $(n/(\log\log n)^{1+\varepsilon}, n^{1-\delta})$-smooth density, where $\varepsilon > 0$ and $0 < \delta < 1$ (note that $(\lceil n^a \rceil, \sqrt{n})$-smooth $\subset$ $(n/(\log\log n)^{1+\epsilon}, n^{1-\delta})$-smooth). The worst-case search and update time is $O(\log n)$, while the worst-case update time can be reduced to $O(1)$ if the update position is given by a finger. Moreover, for several but more restricted than the above smooth densities they can achieve $o(\log\log n)$ expected search and update time complexities; in particular, for the uniform and any bounded distribution the expected search and update time becomes $O(1)$. The above are the best results so far in both the realm of dynamic interpolation structures and the realm of dynamic search tree data structures for μ-random insertions and random deletions on the RAM model.

Based upon dynamic interpolation search, we present in this paper a new finger search tree which, for μ-random insertions and random deletions, achieves $O(1)$ worst-case update time and $O(\log\log d)$ expected search time *with high probability* in the RAM model of computation for the same class of smooth density functions μ considered in [1], thus improving upon the dynamic search structure of Andersson and Mattsson with respect to the expected search time complexity. Moreover, for the same classes of restricted smooth densities considered in [1], we can achieve $o(\log\log d)$ expected search and update time complexities with high probability (e.g., $O(1)$ times for the uniform and any bounded distribution). We would like to mention that the expected bounds in [1, 19] have not been proved to hold with high probability. Our worst-case search time is $O(\sqrt{\log d/\log\log d})$. To the best of our knowledge, this is the first work that uses the dynamic interpolation search paradigm in the framework of finger search trees.

Our data structure is based on a rather simple idea. It consists of two levels: the top level is a tree structure, called *static interpolation search tree* (cf. Section 2) which is similar to the static implicit tree used in [1], while the bottom level consists of a family of buckets. Each bucket is implemented by using the fusion tree technique [8, 26]. However, it is not at all obvious how a combination of these data structures can give better bounds, since deletions of elements may create chains of empty buckets. To alleviate this problem and prove the expected search bound, we use an idea of independent interest. We model the insertions and deletions as a combinatorial game of bins and balls. This combinatorial game is innovative in the sense that it is not used in a load-balancing context, but it is used to model the behaviour of a dynamic data structure as the one we describe in this paper. We provide upper and lower bounds on the number of elements in a bucket and show that, with high probability, a bucket never gets empty. This fact implies that with high probability there cannot exist chains of empty buckets, which in turn allows us to express the search time bound in terms of the parameter d. Note that the combinatorial game presented here is different from the known approaches for balls and bins games (see e.g., [5]), since in those approaches the bins are considered static and the distribution of balls uniform. On the contrary, the bins in our game are random variables since the distribution of balls is unknown. This also makes the initialization of the game a non-trivial task which is tackled by firstly sampling a number of balls and then determining appropriate bins which allow the almost uniform distribution of balls into them.

The remainder of the paper is organized as follows. In Section 2, we discuss preliminary notions and results that are used throughout the paper, and define the static interpolation search tree. Our data structure is presented in Section 3, while the analysis of the time complexities of its operations is discussed in Section 4. The analysis of the combinatorial game, upon which our expected search time is based, is given in Section 5. We conclude in Section 6.

2 Preliminaries

In this paper we consider the unit-cost RAM with a word length of w bits, which models what we program in imperative programming languages such as C. The words of the RAM are addressable and these addresses are stored in memory words, imposing that $w \geq \log n$. As a result, the universe U consists of integers (or reals represented as floating point numbers; see [2]) in the range $[0, 2^w - 1]$. It is also assumed that the RAM can perform the standard AC^0 operations of addition, subtraction, comparison, bitwise Boolean operations and shifts, as well as multiplications in constant worst-case time on $O(w)$-bit operands. One of the main features of the RAM is that the content of the elements are used for addressing, which is one of the basic differences with other comparison based models (such as PM).

In the following, we shall make use of another search tree data structure on a RAM called *q^*-heap* [26]. This data structure is similar to fusion trees [8, 26], but it uses q-heaps instead of an ad-hoc static table in each node of the tree and achieves the same bounds with those of the fusion tree. Let M be the current number of elements in the q^*-heap and let N be an upper bound on the maximum number of elements ever stored in the q^*-heap. Then, insertion, deletion and search operations are carried out in $O(1 + \log M / \log\log N)$ worst-case time after an $O(N)$ preprocessing overhead. Choosing $M = \text{polylog}(N)$, all operations are performed in $O(1)$ time. We will use this structure to guarantee constant worst-case update operations.

In the top level of our data structure we shall use a tree structure, called *static interpolation search tree*, which is an explicit version of the static implicit tree used in [1] and that uses the REP and ID arrays associated with the nodes of IST. More precisely, the *static interpolation search tree* can be fully characterized by three nondecreasing functions $H(n)$, $R(n)$ and $I(n)$. A static interpolation search tree containing n elements has height $H(n)$, the root has out-degree $R(n)$, and there is an ID array associated with the root that has size $I(n) = n \cdot g(H(n))$ such that $\sum_{i=1}^{\infty} g(i) = \Theta(1)$. To guarantee the height of $H(n)$, it should hold that $n/R(n) = H^{-1}(H(n) - 1)$. The children of the root have $n' = \Theta(n/R(n))$ leaves. Their height will be $H(n') = H(n) - 1$, their out-degree is $R(n') = \Theta(H^{-1}(H(n) - 1)/H^{-1}(H(n) - 2))$, and $I(n') = n' \cdot g(H(n'))$. In general, for an internal node v at depth i containing n_i leaves in the subtree rooted at v, we have that $R(n_i) = \Theta(H^{-1}(H(n) - i + 1)/H^{-1}(H(n) - i))$, and $I(n_i) = n_i \cdot g(H(n) - i)$. As in the case of IST [19], each internal node is associated with an array of sample elements REP, one for each of its subtrees, and an ID array. By using the ID array, we can interpolate the REP array to determine the subtree in which the search procedure will continue. In particular, the ID array for node v is an array ID[1..m], where m is some integer, with $\text{ID}[i] = j$ iff $\text{REP}[j] < \alpha + i(\beta - \alpha)/m \leq \text{REP}[j + 1]$, where α and β are the minimum and the maximum element, resp., stored in the subtree rooted at v. Let x be the element we seek. To interpolate REP, compute the index $j = \mathrm{ID}[\lfloor (m(x-\alpha)/(\beta-\alpha)) \rfloor]$, and then scan the REP array from REP$[j+1]$ until the appropriate subtree is located. For each node we explicitly maintain parent, child, and sibling pointers. Pointers to sibling nodes will be alternatively referred to as *level links*. The required pointer information can be easily incorporated in the construction of the static interpolation search tree.

Throughout the paper, we say that an event E occurs *with high probability* if $Pr[E] = 1 - o(1)$.

3 The Data Structure

The data structure consists of two separate structures T_1 and T_2. The former structure guarantees worst-case time bounds while the latter structure guarantees expected time complexities. T_1 is mainly used in the case where the input distribution of elements is not "convenient" and thus T_2 cannot guarantee the expected time complexities. T_2 is attached a flag *active* denoting whether this structure is valid subject to searches and updates, or invalid. In this way, between two global reconstructions of the structure, T_1 stores all available elements while T_2 either stores all elements (*active*=TRUE) or a past instance of the set of elements (*active*=FALSE). T_1 is a finger search tree implemented as in [2] with worst-case $O(1)$ update time and worst-case search time $O(\sqrt{\log d/\log\log d})$. In this way, we can always guarantee worst-case time bounds for searches and updates. In the following we will focus on the structure of T_2.

T_2 is a two-level data structure, similar to the Augmented Sampled Forest (ASF) presented in [1], but with the following differences: (a) we use the static interpolation search tree defined in Section 2; (b) we implement the buckets associated with the leaves of the static interpolation search tree using q^*-heaps, instead of simple binary search trees; (c) our search procedure does not start from the root of the tree, but we are guided by a finger f to start from an arbitrary leaf; and (d) our reconstruction procedure to maintain our data structure is quite different from that used in [1]. More specifically, let S_0 be the set of elements to be stored where the elements take values in $[a, b]$. The two levels of T_2 are as follows. The bottom level is a set of ρ buckets. Each bucket $\mathcal{B}_i$, $1 \le i \le \rho$, stores a subset of elements and is represented by the element $rep(i) = \max\{x : x \in \mathcal{B}_i\}$. The set of elements stored in the buckets constitute an ordered collection $\mathcal{B}_1, \ldots, \mathcal{B}_\rho$ such that $\max\{x : x \in \mathcal{B}_i\} < \min\{y : y \in \mathcal{B}_{i+1}\}$ for all $1 \le i \le \rho - 1$. In other words, $\mathcal{B}_i = \{x : x \in (rep(i-1), rep(i)]\}$, for $2 \le i \le \rho$, and $\mathcal{B}_1 = \{x : x \in [rep(0), rep(1)]\}$, where $rep(0) = a$ and $rep(\rho) = b$. Each $\mathcal{B}_i$ is implemented as a q^*-heap [26]. The top level data structure is a static interpolation search tree that stores all elements.

Our data structure is maintained by incrementally performing global reconstructions [20]. More precisely, let S_0 be the set of stored elements at the latest reconstruction, and assume that $S_0 = \{x_1, \ldots, x_{n_0}\}$ in sorted order. The reconstruction is performed as follows. We partition S_0 into two sets S_1 and S_2, where $S_1 = \{x_{i \cdot \ln n_0} : i = 1, \ldots, \frac{n_0}{\ln n_0} - 1\} \cup \{b\}$, and $S_2 = S_0 - S_1$. The i-th element of S_1 is the representative $rep(i)$ of the i-th bucket $\mathcal{B}_i$, where $1 \le i \le \rho$ and $\rho = |S_1| = \frac{n_0}{\ln n_0}$. An element $x \in S_2$ is stored twice: (i) In the appropriate bucket $\mathcal{B}_i$, iff $rep(i-1) < x \le rep(i)$, for $2 \le i \le \frac{n_0}{\ln n_0}$; otherwise ($x \le rep(1)$), x is stored in $\mathcal{B}_1$. (ii) As a leaf in the top level structure where it is marked redundant and is equipped with a pointer to the representative of the bucket to which it belongs. We also mark as redundant all internal nodes of the top level structure that span redundant leaves belonging to the same bucket and equip them with a pointer to the representative of the bucket. The reason we store the elements of S_2 twice is to ensure that all elements are drawn from the same μ-random distribution and hence we can safely apply the analysis presented in [1, 19]. Also, the reason for this kind of representatives will be explained in Section 5. Note

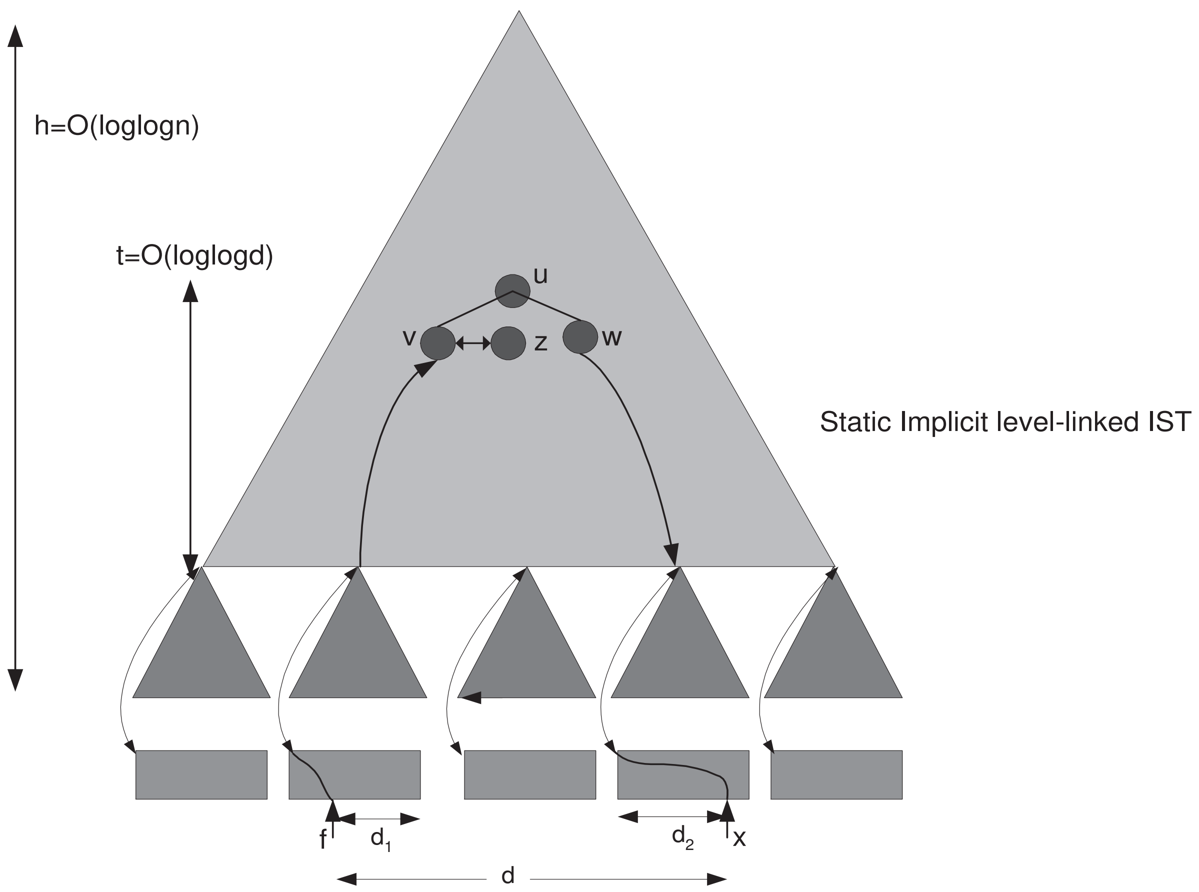

Figure 1: The search path from finger f to key x.

that, after reconstruction, each new element is stored only in the appropriate bucket. Each time the number of updates exceeds rn_0, where r is an arbitrary constant, the whole data structure is reconstructed. Let n be the number of stored elements at this time. After the reconstruction, the number of buckets is equal to $\frac{n}{\ln n}$ and the value of the parameter N, used for the implementation of $\mathcal{B}_i$ with a q^*-heap, is n. Immediately after the reconstruction, if every bucket stores less than polylog(n) elements, then *active*=TRUE, otherwise *active*=FALSE.

In order to insert/delete an element immediately to the right of an existing element f, we insert/delete the element to/from T_1 (using the procedures in [2]), and we insert/delete the element to/from the appropriate bucket of T_2 if *active*=TRUE (using the procedures in [26]). If during an insertion in a bucket of T_2, the number of stored elements becomes greater than polylog(n), then *active*=FALSE.

The search procedure for locating an element x in the data structure, provided that a finger f to some element is given, is carried out as follows. If *active*=TRUE, then we search in parallel both structures and we stop when we first locate the element, otherwise we only search in T_1. The search procedure in T_1 is carried out as in [2]. The search procedure in T_2 involves a check as to whether x is to the left or to the right of f. Assume, without loss of generality, that x is to the right of f (see Figure 1). Then, we have two cases:

1. Both elements belong to the same bucket $\mathcal{B}_i$. In this case, we just retrieve from the q^*-heap

that implements $\mathcal{B}_i$ the element with key x.

2. The elements are stored in different buckets $\mathcal{B}_i$ and $\mathcal{B}_j$ containing f and x respectively. In this case, we start from $rep(i)$ and we walk towards the root of the static interpolation search tree. Assuming that we reach a node v, we check whether x is stored in a descendant of v or in the right neighbour z of v. This can be easily accomplished by checking the boundaries of the REP arrays of both nodes. If they are not stored in the subtrees of v and z, then we proceed to the parent of v, otherwise we continue the search in the particular subtree using the ID and REP arrays. When a redundant node is reached, we follow its associated pointer to the appropriated bucket.

4 Analysis of Time and Space Complexity

In this section we analyze the time complexities of the search and update operations. For reasons of simplicity, we start with the case of $(n/(\log\log n)^{1+\epsilon}, n^{1-\delta})$-smooth densities, and later on discuss how our result can be extended to the general case of $(n \cdot g(H(n)), H^{-1}(H(n)-1))$-smooth densities, where $H(n)$ is an increasing function representing the height of the static interpolation tree and g is a function satisfying $\sum_{i=1}^{\infty} g(i) = \Theta(1)$.

The tree structure T_2 is updated and queried only in the case where all of its buckets have size polylog(n) (*active*=TRUE), where n is the number of elements in the latest reconstruction. By this and by using some arguments of the analysis in [2] and [26] the following lemma is immediate.

Lemma 1 *The preprocessing time and the space usage of our data structure is $\Theta(n)$. The update operations are performed in $O(1)$ worst-case time.*

The next theorem gives the time complexity of our search operation.

Theorem 1 *Suppose that the top level of T_2 is a static interpolation search tree with parameters $R(s_0) = (s_0)^\delta$, $I(s_0) = s_0/(\log\log s_0)^{1+\epsilon}$, where $\epsilon > 0$, $0 < \delta < 1$, and $s_0 = \frac{n_0}{\ln n_0}$ with active=TRUE. Then, the expected time complexity of a search operation is equal to $O(\min\{\frac{\log|\mathcal{B}_i|}{\log\log n} + \frac{\log|\mathcal{B}_j|}{\log\log n} + \log\log d, \sqrt{\log d/\log\log d}\})$, with high probability, where $\mathcal{B}_i$ and $\mathcal{B}_j$ are the buckets containing the finger f and the search element x respectively, d denotes the number of buckets between $\mathcal{B}_i$ and $\mathcal{B}_j$, and n denotes the current number of elements.*

Proof. It is clear from the description of the search procedure that since *active*=TRUE the search time is the minimum of the search time for each of the structures T_1 and T_2. The search operation in T_1 is performed in $O(\sqrt{\log d/\log\log d})$ time. The search operation in T_2 can be decomposed into three basic steps (see also Figure 1): (i) the search for x in the q^*-heap implementing $\mathcal{B}_i$, (ii) the traversal of internal nodes of the static interpolation search tree, using ancestor pointers, level links and interpolation search, and (iii) the search for x in the q^*-heap implementing $\mathcal{B}_j$, where $x \in \mathcal{B}_j$.

The time complexity for the execution of steps (i) and (iii) is equal to $O(\frac{\log|\mathcal{B}_i|}{\log\log n_0} + \frac{\log|\mathcal{B}_j|}{\log\log n_0})$, where n_0 is the number of stored elements at the latest reconstruction. Since $\log\log n_0 = \Theta(\log\log n)$, this time complexity is equal to $O(\frac{\log|\mathcal{B}_i|}{\log\log n} + \frac{\log|\mathcal{B}_j|}{\log\log n})$. Suppose that for step (ii) we stop the ascension of the search procedure at node u, coming from child v and descending to child w (cf. Fig.1). It is clear that between v and w there must exist at least one separating node, call it z, otherwise we should stop the traversal at a lower height. Let u_l and z_l be the number of buckets in the subtrees rooted at u and z respectively and let t be the height of u without taken into account redundant nodes. It is easy to see that $z_l \leq d \leq u_l$. Since $t = O(\log\log u_l)$ and $z_l = (u_l)^\delta$, we conclude that $(O(2^{2^t}))^\delta \leq d \leq O(2^{2^t})$. Since the exponent δ, when considered in the double logarithmic time complexity, becomes an additive term, and since in Theorem 6 we will show that with high probability no bucket gets empty we deduce that the time complexity in the ascent phase of step (ii) is $O(\log\log d)$ with high probability. In the following, we will prove (by exploiting the probabilistic analysis in [19]) that the time complexity of the descent phase in step (ii) is $O(\log\log d)$ with high probability and the theorem will follow.

Consider the descent phase of step (ii). During the descent the algorithm visits a path P of t nodes with the last node being the root of a subtree with $\log n$ elements. Let $v_1, \ldots, v_t$ be the nodes in the path listed in order of visit and consider a node v_i randomly selected in the path. Let n_i be the number of leaves in the subtree with root v_i. It is clear that for every i, $n_i \geq \log n$. In [19] it was proven that, for the special case where $\delta = 1/2$ there is a constant c such that the probability that the interpolation procedure takes in v_i more than l steps is bounded from above by $(\frac{c}{l})^{l\sqrt{n}_i}$. Their analysis can be immediately extended in order to prove that for arbitrary δ there is a constant c such that the probability that the interpolation procedure takes in v_i more than l steps is bounded from above by $(\frac{c}{l})^{ln_i^{1-\delta}}$. For $l = 2c$ the above bound becomes $(\frac{1}{2})^{2cn_i^{1-\delta}}$. Let q be the probability that there is a node in P for which interpolating takes more than $2c$ steps. Then, it follows that $q \leq \sum_{i=1}^{t}(\frac{1}{2})^{2cn_i^{1-\delta}} \leq t(\frac{1}{2})^{2c(\log n)^{1-\delta}}$. Hence, for the probability p that the descent phase takes less than $2ct$ steps we have $p \geq 1 - t(\frac{1}{2})^{2c(\log n)^{1-\delta}}$. Since $t = O(\log\log d) = O(\log\log n)$ we get: $t(\frac{1}{2})^{2c(\log n)^{1-\delta}} \to 0$, as n grows, and thus we conclude that the descent phase in step (ii) takes $2ct = O(\log\log d)$ expected time with high probability. ■

In order to prove that the data structure has a small expected search time with high probability we introduce a combinatorial game of balls and bins with deletions (Section 5). To obtain the desirable time complexities with high probability, we provide upper and lower bounds on the number of elements in a bucket and we show that no bucket gets empty (see Theorem 6). Combining Theorems 1 and 6 we get the main result of the paper.

Theorem 2 *There exists a finger search tree with $O(\log\log d)$ expected search time with high probability for μ-random insertions and random deletions, where μ is a $(n/(\log\log n)^{1+\varepsilon}, n^{1-\delta})$-smooth density for $\varepsilon > 0$ and $0 < \delta < 1$, and d is the distance between the finger and the search element. The space usage of the data structure is $\Theta(n)$, the worst-case update time is $O(1)$, and the worst-case search time is $O(\sqrt{\log d/\log\log d})$.*

Our analysis so far focused on the particular class of $(n/(\log\log n)^{1+\epsilon}, n^{1-\delta})$-smooth densities where $\epsilon > 0$ and $0 < \delta < 1$. However, we can generalize our results to hold for the general class of smooth densities considered in [1], thus being able to achieve $o(\log\log d)$ expected time complexity, with high probability, for several distributions. More specifically, by examining the proof of Theorem 1, we can see that the specific choice of the class of smooth densities comes into play when analyzing step (ii) of the search procedure in T_2. In the rest of this section we sketch the proof of the general class of densities.

Let t denote the time complexity of step (ii). We can generalize the proof by applying the following argument: let $h(z)$ be the height of z (without taken into account the redundant nodes in its subtree) and $h(u)$ be the height of u (without taken into account again reduntant nodes). Let z_l be the number of buckets in the subtree rooted at z and let u_l be the number of buckets in the subtree rooted at u. Then the following hold:

(i) $t = O(h(u))$; (ii) $z_l \leq d \leq u_l \Rightarrow h(z) \leq H(d) \leq h(u)$; and (iii) $h(u) = h(z) + 1$.

From (i) and (iii) we get that $t = O(h(z))$ and from (ii) we get $t = O(H(d))$. The above discussion establishes the following theorem.

Theorem 3 *There exists a finger search tree with $\Theta(H(d))$ expected search time with high probability for μ-random insertions and random deletions, where d is the distance between the finger and the search element, and μ is a $(n \cdot g(H(n)), H^{-1}(H(n) - 1))$-smooth density, where $\sum_{i=1}^{\infty} g(i) = \Theta(1)$. The space usage of the data structure is $\Theta(n)$, the worst-case update time is $O(1)$, and the worst-case search time is $O(\sqrt{\log d / \log\log d})$.*

For example, the density $\mu[0,1](x) = -\ln x$ is $(n/(\log^* n)^{1+\epsilon}, \log^2 n)$-smooth, and for this density $R(n) = n/\log^2 n$. This means that the height of the tree with n elements is $H(n) = \Theta(\log^* n)$ and the method of [1] gives an expected search time complexity of $\Theta(\log^* n)$. However, by applying Theorem 3, we can reduce the expected time complexity for the search operation to $\Theta(\log^* d)$ and this holds with high probability. If μ is bounded, then it is $(n, 1)$-smooth and hence $H(n) = O(1)$, implying the same expected search time with [1] but with high probability.

5 A Combinatorial Game of Bins and Balls with Deletions

In this section we describe a balls-in-bins random process that models each update operation in the structure T_2 presented in Section 3. Consider the structure T_2 immediately after the latest reconstruction. It contains the set S_0 of n elements (we shall use n for notational simplicity) which are drawn randomly according to the distribution $\mu(\cdot)$ from the interval $[a, b]$. The next reconstruction is performed after rn update operations on T_2, where r is a constant. Each update operation is either a uniformly at random deletion of an existing element from T_2, or a μ-random insertion of a new element from $[a, b]$ into T_2. To model the update operations as a balls-in-bins random process, we do the following.

We represent each selected element from $[a, b]$ as a *ball*. We partition the interval $[a, b]$ into $\rho = \frac{n}{\ln n}$ parts $[rep(0), rep(1)] \cup (rep(1), rep(2)] \cup \ldots \cup (rep(\rho - 1), rep(\rho)]$, where $rep(0) = a$, $rep(\rho) = b$, and $\forall i = 1, \ldots, \rho - 1$, the elements $rep(i) \in [a, b]$ are those defined in Section 3. We represent each of these ρ parts as a distinct *bin*.

During each of the rn insertion/deletion operations in T_2, a μ-random ball $x \in [a, b]$ is inserted in (deleted from) the i-th bin $\mathcal{B}_i$ iff $rep(i-1) < x \leq rep(i)$, $i = 2, \ldots, \rho$, otherwise x is inserted in (deleted from) $\mathcal{B}_1$.

5.1 Almost Uniform Bins

Our aim is to prove that with high probability (w.h.p.) the maximum load of any bin is $O(\ln n)$, and that no bin remains empty as $n \to \infty$. If we were knowing the distribution $\mu(\cdot)$, then we could partition the interval $[a, b]$ into $\rho = \frac{n}{\ln n}$ distinct bins (parts), $[rep_\mu(0), rep_\mu(1)] \cup (rep_\mu(1), rep_\mu(2)] \cup \ldots \cup (rep_\mu(\rho - 1), rep_\mu(\rho)]$, with $rep_\mu(0) = a$ and $rep_\mu(\rho) = b$, such that a μ-random ball x would be equally likely to belong into any of the ρ corresponding bins. In other words, since these ρ bins have equal probability to receive ball x, we have that $\forall x \in [a, b]$ it holds:

$$Pr[x \in (rep_\mu(i-1), rep_\mu(i)]] = \int_{rep_\mu(i-1)}^{rep_\mu(i)} \mu(t)dt = \frac{1}{\rho} = \frac{\ln n}{n}, \quad i = 1, \ldots, \rho = \frac{n}{\ln n}.$$

Remark 1 *The above expression implies that the unknown sequence $rep_\mu(0), \ldots, rep_\mu(\rho)$ makes the event "insert (delete) a μ-random (random) element x into (from) the structure" equivalent to* *the event "throw (delete) a ball uniformly at random into (from) one of ρ distinct bins". Such a uniform distribution of balls into bins is well understood and it is folklore to find conditions such that no bin remains empty and no bin gets more than $O(\ln n)$ balls.*

Unfortunately, the probability density $\mu(\cdot)$ is unknown. Consequently, our goal is to *approximate* the unknown sequence $rep_\mu(0), \ldots, rep_\mu(\rho)$ with a sequence $rep(0), \ldots, rep(\rho)$, that is, to partition the interval $[a, b]$ into ρ parts $[rep(0), rep(1)] \cup (rep(1), rep(2)] \cup \ldots \cup (rep(\rho-1), rep(\rho)]$, aiming to prove that each bin (part) will have the key property:

$$Pr[x \in (rep(i-1), rep(i)]] = \int_{rep(i-1)}^{rep(i)} \mu(t)dt = \Theta\left(\frac{1}{\rho}\right) = \Theta\left(\frac{\ln n}{n}\right), \ i = 1, \ldots, \rho.$$

Remark 2 *The sequence $rep(0), \ldots, rep(\rho)$ makes the event "insert (delete) a μ-random (random) element x into (from) the structure" equivalent to the event "throw (delete) a ball* almost *uniformly at random into one of ρ distinct bins". This fact will become the cornerstone in our subsequent proof that no bin remains empty and almost no bin gets more than $\Theta(\ln n)$ balls.*

An illustration of Remarks 1 and 2 is given in Fig. 2. The basic insight of our approach is illustrated

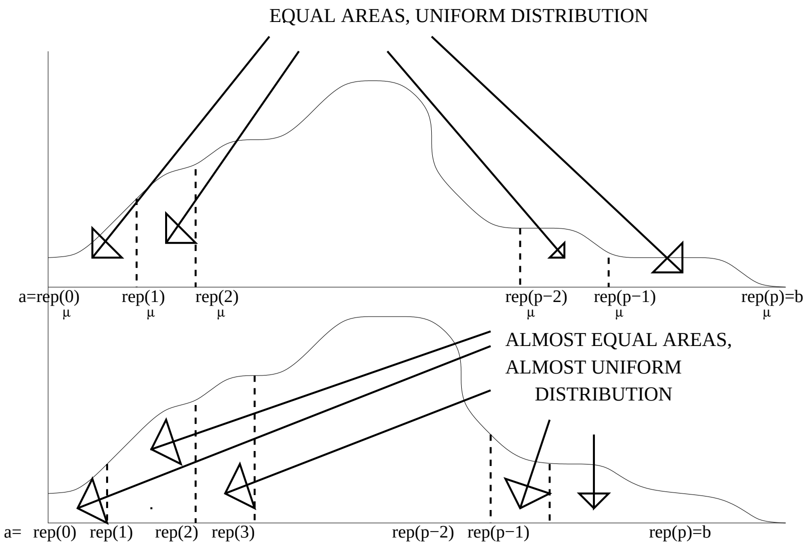

Figure 2: Plot of an unknown probability density $\mu(x), x \in [a, b]$. The upper graphic represents the uniform bins defined by: $rep_\mu(0), rep_\mu(1), \ldots, rep_\mu(\rho)$. The lower graphic represents the *almost* uniform bins defined by: $rep(0), rep(1), \ldots, rep(\rho)$.

by the following random game. Consider the part of the horizontal axis spanned by $[a, b]$, which will be referred to as the $[a, b]$ *axis*. Suppose that only a wise man knows the positions on the $[a, b]$ axis of the sequence $rep_\mu(0), \ldots, rep_\mu(\rho)$, referred to as the *red dots*. Next, perform n independent insertions of μ-random elements from $[a, b]$ (this is the role of the set S_0). In each insertion of an element x, we add a *blue dot* in its position on the $[a, b]$ axis. At the end of this random game we have a total of n blue dots in this axis. Now, the wise man reveals the red dots on the $[a, b]$ axis, i.e., the sequence $rep_\mu(0), \ldots, rep_\mu(\rho)$. If we start counting the blue dots *between* any two consecutive red dots $rep_\mu(i-1)$ and $rep_\mu(i)$, we almost always find that there are $\ln n + o(1)$ blue dots. This is because the number X_i^μ of μ-random elements (blue dots) selected from $[a, b]$ that belong in $(rep_\mu(i-1), rep_\mu(i)]$, $i = 1, \ldots, \rho$, is a Binomial random variable, $X_i^\mu \sim B(n, \frac{1}{\rho} = \frac{\ln n}{n})$, which is sharply concentrated to its expectation $E[X_i^\mu] = \ln n$.

The above discussion suggests the following procedure for constructing the sequence $rep(0), \ldots,$ $rep(\rho)$. Partition the sequence of n blue dots on the $[a, b]$ axis into $\rho = \frac{n}{\ln n}$ parts, each of size $\ln n$. Set $rep(0) = a$, $rep(\rho) = b$, and set as $rep(i)$ the $i \cdot \ln n$-th blue dot, $i = 1, \ldots, \rho - 1$. Call this procedure `Red-Dots`.

Remark 3 *The above intuitive argument does not imply that $\lim_{n\to\infty} rep(i) = rep_\mu(i)$, $\forall i = 0, \ldots, \rho$. Clearly, since $rep_\mu(i)$, $i = 0, \ldots, \rho$, is a real number, the probability that at least one blue dot* hits *an invisible red dot is insignificant. The above argument stresses on the crucial fact that the probability measure enclosed in the random interval $(rep(i-1), rep(i)]$, $i = 1, \ldots, \rho$, must be of order $\Theta\left(\frac{1}{\rho}\right) = \Theta\left(\frac{\ln n}{n}\right)$, regardless of the particular distribution density $\mu(\cdot)$.*

Theorem 4 *Let $rep(0), rep(1), \ldots, rep(\rho)$ be the output of procedure* `Red-Dots`*, and let $p_i(n) = \int_{rep(i-1)}^{rep(i)} \mu(t)dt$. Then:*

$$\Pr\left[\exists\ i \in \{1, \ldots m\} : p_i(n) \neq \Theta\left(\frac{1}{\rho}\right) = \Theta\left(\frac{\ln n}{n}\right)\right] \to 0.$$

Proof. Let $\alpha(n) = \ln n/n$. Without loss of generality, we compute the probability that a block of $\ln n = \alpha(n)n$ consecutive blue dots is spread into a sub-interval (part) of the $[a, b]$ axis of probability measure $q(n)$. This probability equals

$$\binom{n}{\alpha(n)n} q(n)^{\alpha(n)n}(1-q(n))^{(1-\alpha(n))n} \sim \left[\left(\frac{q(n)}{\alpha(n)}\right)^{\alpha(n)}\left(\frac{1-q(n)}{1-\alpha(n)}\right)^{1-\alpha(n)}\right]^n \tag{1}$$

where the expression on the right is asymptotically equal to the expression on the left if we use Stirling's approximation $n! \sim \left(\frac{n}{e}\right)^n\sqrt{2\pi n}$ and ignore inverse polynomial multiplicative terms. Expression (1) is a convex function of two variables ($q(n)$ and $\alpha(n)$) and achieves its maximum when $q(n) = \alpha(n)$. Hence, the expression vanishes exponentially with n, when either $q(n) = o(\alpha(n))$ or $q(n) = \omega(\alpha(n))$. There are $\rho = \frac{n}{\ln n}$ blocks of $\ln n$ consecutive blue dots. Applying the first moment method, we get that the probability that at least one block has its $\ln n$ blue dots spread into a sub-interval of $[a, b]$ axis of measure $q(n)$ is at most

$$\frac{n}{\ln n} \cdot \left[\left(\frac{q(n)}{\alpha(n)}\right)^{\alpha(n)}\left(\frac{1-q(n)}{1-\alpha(n)}\right)^{1-\alpha(n)}\right]^n \to 0, \tag{2}$$

as n approaches infinity. We conclude that it is very unlikely that the probability measure $p_i(n)$ of each part $(rep(i-1), rep(i)]$, $i = 1, \ldots, \rho$, defined by the sequence $rep(0), rep(1), \ldots, rep(\rho)$, will be different from $\Theta(1/\rho) = \Theta(\ln n/n)$. ∎

The above discussion and Theorem 4 imply the following.

Corollary 1 *If n elements are μ-randomly* selected *from $[a, b]$, and the sequence $rep(0), \ldots, rep(\rho)$ from those elements is produced by procedure* `Red-Dots`*, then this sequence partitions the interval $[a, b]$ into ρ distinct bins (parts) $[rep(0), rep(1)] \cup (rep(1), rep(2)] \cup \ldots \cup (rep(\rho-1), rep(\rho)]$ such that a ball $x \in [a, b]$ can be thrown (deleted)* independently *of any other ball in $[a, b]$ into (from) any of the bins with probability $p_i(n) = \Pr[x \in (rep(i-1), rep(i)]] = \frac{c_i \ln n}{n}$, where $i = 1, \ldots, \rho$ and c_i is a positive constant.*

Definition 1 *Let $c = \min_i\{c_i\}$ and $C = \max_i\{c_i\}$, $i = 1, \ldots, \rho$, where $c_i = \frac{np_i(n)}{\ln n}$.*

5.2 Randomness Invariance

In this section, we study the randomness properties in each of the rn subsequent insertion/deletion operations on the structure T_2 (r is a constant).

Observe that before the process of rn insertions/deletions starts, each bin $\mathcal{B}_i$ (i.e., part $(rep(i-1), rep(i)]$) contains exactly $\ln n$ balls (blue dots on the $[a,b]$ axis) of the n initial balls of the set S_0. For convenience, we analyze a slightly different process of the subsequent rn insertions/deletions. Delete all elements (balls) of S_0 except for the representatives $rep(0), rep(1), \ldots, rep(\rho)$ of the ρ bins. Then, insert μ-randomly n/c (see Definition 1) new elements (balls) and subsequently start performing the rn insertions/deletions. Since the n/c new balls are thrown *μ-randomly* into the ρ bins $[rep(0), rep(1)] \cup (rep(1), rep(2)] \cup \ldots \cup (rep(\rho-1), rep(\rho)]$, by Corollary 1 the initial number of balls into $\mathcal{B}_i$ is a Binomial random variable that obeys $B(n/c, p_i(n))$, $i = 1, \ldots, \rho$, instead of being fixed to the value $\ln n$. Clearly, if we prove that for this process no bin remains empty and does not contain more than $O(\ln n)$ balls, then this also holds for the initial process.

Definition 2 *Let the random variable $M(j)$ denote the number of balls existing in structure T_2 at the end of the j-th insertion/deletion operation, $j = 0, \ldots, rn$. Initially, $M(0) = n/c$.*

The next useful lemma allows us to keep track of the statistics of an arbitrary bin.

Lemma 2 *Suppose that at the end of j-th insertion/deletion operation there exist $M(j)$ distinct balls that are μ-randomly distributed into the ρ distinct bins. Then, after the $(j+1)$-th insertion/deletion operation the $M(j+1)$ distinct balls are also μ-randomly distributed into the ρ distinct bins.*

Proof. We use induction on j. The lemma trivially holds for $j = 0$. That is, independently (by Corollary 1) each ball $x \in [a,b]$ of the initial $M(0) = n/c$ balls belongs into $\mathcal{B}_i$ with probability $p_i(n) = c_i/\rho = c_i \ln n/n$, $i = 1, \ldots, \rho$. Suppose that it holds for the $M(j)$ balls when $j = k$. That is, each ball x, of the $M(k)$ existing balls, belongs into $\mathcal{B}_i$ with probability $p_i(n)$, $i = 1, \ldots, \rho$. We prove the lemma for $j = k+1$.

If the $(k+1)$-th operation is insertion then the current number of balls is $M(k+1) = M(k)+1$. By Corollary 1, the *new* inserted ball x' belongs into $\mathcal{B}_i$ independently with probability $p_i(n)$, $i = 1, \ldots, \rho$. For the same reason, each ball x, of the $M(k)$ *old* balls, belongs into $\mathcal{B}_i$ independently with probability $p_i(n)$, $i = 1, \ldots, \rho$. We conclude that at the end of the $(k+1)$-th operation, each ball x of the total $M(k+1) = M(k)+1$ balls belongs into $\mathcal{B}_i$ independently with probability $p_i(n)$.

If the $(k+1)$-th operation is deletion then the current number of balls is $M(k+1) = M(k) - 1$. Due to Corollary 1, each ball x, of the $M(k) - 1$ remaining balls, belongs into $\mathcal{B}_i$ independently with probability $p_i(n)$, $i = 1, \ldots, \rho$.

We conclude that at the end of the $(k+1)$-th operation, each ball x of the current $M(k+1)$ balls, belongs into $\mathcal{B}_i$ independently with probability $p_i(n)$, $i = 1, \ldots, \rho$. ∎

An immediate consequence of Lemma 2 is the following lemma.

Lemma 3 *Let the random variable $Y_i(j)$ with $(i,j) \in \{1, \ldots, \rho\} \times \{0, \ldots, rn\}$ denote the number of balls that the i-th bin contains at the end of the j-th operation. Then, $Y_i(j) \sim B(M(j), p_i(n))$.*

5.3 Dynamics of $M(j)$

We want to study the dynamics of the current number of balls $M(j)$ existing in the structure T_2 at the end of j-th operation, $j = 0, \ldots, rn$; that is, we wish to approximate this number with high probability, for each insertion/deletion operation $j = 0, \ldots, rn$. In each operation, a ball is either inserted with probability $p > 1/2$, or is deleted with probability $1 - p$. $M(j)$ is a discrete random variable which has the nice property of sharp concentration to its expected value, i.e., it has small deviation from its mean compared to the total number of operations.

In the following, instead of working with the actual values of j and $M(j)$, we shall use their *scaled* (divided by n) values t and $m(t)$, resp., that is, $t = \frac{j}{n}$, $m(t) = \frac{M(tn)}{n}$, with range $(t, m(t)) \in [0, r] \times [1, m(r)]$. The following theorem provides an estimation on $m(t)$.

Theorem 5 *For each operation $0 \leq t \leq r$, the scaled number of balls that are distributed into the $\frac{n}{\ln(n)}$ bins at the end of the t-th operation equals $m(t) = (2p - 1)t + o(1)$, with high probability.*

Proof. Let the random variable $\gamma^+ tn$, $\gamma^+ \in [0, 1]$, denote the current fraction of insertion operations among the currently performed tn operations, and let $\gamma^- tn$ denote the remaining fraction of deletion operations. Clearly, $\gamma^+ + \gamma^- = 1$. The number $M(j) = M(tn)$ of balls that are distributed into the bins at the end of j-th operation equals the number $\gamma^+ tn$ of insertions minus the number $\gamma^- tn$ of deletions. Consequently, $M(j) = M(tn) = (\gamma^+ - \gamma^-)tn = (\gamma^+ - (1 - \gamma^+))tn = (2\gamma^+ - 1)tn$. Therefore, $M(tn)$ depends solely on the random variable $\gamma^+ tn$. Since in each of the tn operations a ball is inserted with probability p, the random variable $\gamma^+ tn$ of currently inserted balls obeys the binomial $B(tn, p)$ distribution. As a result, the random variable $\gamma^+ tn$ is sharply concentrated to its expected value ptn. That is, $\gamma^+ tn \to ptn$ with high probability, as $n \to \infty$. Equivalently, $\gamma^+ \to p$ with high probability, as $n \to \infty$. ∎

Remark 4 *Observe that for $p > 1/2$, $m(t)$ is an increasing positive function of the scaled number t of operations, that is, $\forall\, t \geq 0$, $M(tn) = m(t)n \geq M(0) = m(0)n = n/c$.*

Remark 4 implies that if no bin remains empty before the process of rn operations starts, since for $p > 1/2$ the balls accumulate as the process evolve, then no bin will remain empty in each subsequent operation. This is important on proving part (i) of Theorem 6.

5.4 Statistics of the Bins

In this section, we prove that before the first operation, and for all subsequent operations, with high probability, no bin remains empty. Furthermore, we prove that during each step the maximum load of any bin is $\Theta(\ln(n))$ with high probability. For the analysis below we make use of the Lambert function $LW(x)$, which is the analytic at zero solution with respect to y of the equation: $ye^y = x$ (see [6]). Recall also that during each operation $j = 0, \ldots, rn$ with probability $p > 1/2$ we insert a μ-random ball $x \in [a, b]$, and with probability $1 - p$ we delete an existing ball from the current $M(j)$ balls that are stored in the structure T_2.

Theorem 6 *(i) For each operation $0 \leq t \leq r$, let the random variable $X(t)$ denote the current number of empty bins. If $p > 1/2$, then for each operation t, $E[X(t)] \to 0$.*
(ii) At the end of operation t, let the random variable $Z_\kappa(t)$ denote the number of bins with load at least $\kappa \ln(n)$, where $\kappa = \kappa(t)$ satisfies $\kappa \geq (-Cm(t) + 2)/(C \cdot LW(-\frac{Cm(t)-2}{Cm(t)e})) = O(1)$, and C is the positive constant defined in Definition 1. If $p > 1/2$, then for each operation t, $E[Z_\kappa(t)] \to 0$.

Proof. (i) Recall the definitions of the positive constants c and C (Definition 1, at the end of Section 5.1). From Lemmata 2 and 3, $\forall\, i = 1, \ldots, \rho = \frac{n}{\ln(n)}$, it holds:

$$Pr[Y_i(t) = 0] \leq \left(1 - c\frac{\ln(n)}{n}\right)^{m(t)n} \sim e^{-cm(t)\ln(n)} = \frac{1}{n^{cm(t)}}. \tag{3}$$

From Eq. (3), by linearity of expectation, we obtain:

$$E[X(t) \mid m(t)] \le \sum_{i=1}^{\rho} Pr[Y_i(t) = 0] \le \frac{n}{\ln(n)} \cdot \frac{1}{n^{cm(t)}}. \tag{4}$$

From Theorem 5 and Remark 4 it holds:

$$\forall\, t \ge 0,\ \frac{1}{n^{cm(t)}} \le \frac{1}{n^{cm(0)}} = \frac{1}{n}.$$

This inequality implies that in order to show for each operation t that the expected number $E[X(t) \mid m(t)]$ of empty bins vanishes, it suffices to show that before the process starts, the expected number $E[X(0) \mid m(0)]$ of empty bins vanishes. In this line of thought, from Theorem 5, Eq. (4) becomes,

$$E[X(0) \mid m(0)] \le \frac{n}{\ln(n)} \cdot \frac{1}{n^{cm(0)}} = \frac{n}{\ln(n)} \cdot \frac{1}{n} = \frac{1}{\ln(n)} \to 0.$$

Finally, from Markov's inequality, we obtain

$$Pr[X(t) > 0 \mid m(t)] \le E[X(t) \mid m(t)] \le E[X(0) \mid m(0)] \to 0.$$

(ii) At the end of t-th operation, with high probability $m(t)n$ balls are distributed amongst the ρ distinct bins. By Lemma 3, an arbitrary $\mathcal{B}_i$ is expected to contain $Y_i(t) = \Theta(m(t)\ln(n))$ balls, $i = 1, \ldots, \rho$. Let $\mathcal{B}_{i'}$ be one of the bins that attains the maximum probability $p_{i'}(n) = C\frac{\ln n}{n}$ to receive a ball per insertion operation.

To prove that the expected number $E[Z_\kappa(t) \mid m(t)]$ of bins containing more than $\kappa\ln(n)$ balls converges to 0, it suffices to prove that for all $i = 1, \ldots, \rho$, the probability of any $\mathcal{B}_i$ to contain $Y_i(t) \ge \kappa\ln(n) > m(t)\ln(n)$ is exponentially small, for $\kappa \ge -\frac{Cm(t)-2}{C\cdot LW(-\frac{Cm(t)-2}{Cm(t)e})}$. It suffices to prove this for $\mathcal{B}_{i'}$ which is the most likely to receive balls. To this end,

$$Pr[Y_{i'}(t) \ge \kappa\ln(n) |\ m(t)] = \sum_{j=\kappa\ln(n)}^{m(t)n} Pr[Y_{i'}(t) = j \mid m(t)]. \tag{5}$$

From Lemma 3, $Y_{i'}(t)$ is a Binomial random variable. Introducing the deviation function $\delta = \delta(n)$ with range in $(0, 1)$, we get:

$$Pr[Y_{i'}(t) = \delta m(t)n |\ m(t)n] = \binom{m(t)n}{\delta m(t)n} \left(C\frac{\ln(n)}{n}\right)^{\delta m(t)n} \left(1 - C\frac{\ln(n)}{n}\right)^{(1-\delta)m(t)n}.$$

Applying Stirling's approximation: $n! \sim \sqrt{2\pi n}e^{-n}n^n$ and ignoring inverse polynomial multiplicative terms we obtain:

$$Pr[Y_{i'}(t) = \delta m(t)n |\ m(t)n] \sim \left[\left(C\frac{\ln(n)}{\delta n}\right)^{\delta} \left(\frac{n - C\ln(n)}{(1-\delta)n}\right)^{(1-\delta)}\right]^{m(t)n}.$$

Since we want to study the deviation $\kappa\ln(n)$ of $Y_{i'}(t)$ from its expected value $m(t)C\ln(n)$ we set the function $\delta = \delta(n) = \frac{\kappa C\ln(n)}{m(t)n}$. In this way, we have that

$$Pr[Y_{i'}(t) = \delta m(t)n |\ m(t)n] \quad = \quad Pr[Y_{i'}(t) = \kappa\ln(n) |\ m(t)n]$$

$$
\begin{aligned}
&\sim \left[\left(\frac{m(t)}{\kappa}\right)^{\frac{\kappa C\ln(n)}{m(t)n}}\left(\frac{n-C\ln(n)}{n-\kappa C\ln(n)/m(t)}\right)^{\frac{m(t)n-\kappa C\ln(n)}{m(t)n}}\right]^{m(t)n}\\
&\sim \left(\frac{m(t)}{\kappa}\right)^{\kappa C\ln(n)} e^{(\kappa-m(t))C\ln(n)}e^{\frac{\ln^2(n)}{n}C(\kappa-\kappa^2/m(t))}\\
&\sim \left(\left(\frac{m(t)}{\kappa}\right)^{\kappa C} e^{C(\kappa-m(t))}\right)^{\ln(n)}.
\end{aligned}
$$

Therefore, for $\kappa > Cm(t)$, and by noticing that the probability density function of $Y_{i'}(t)$ has a unique maximum at the point $E[Y_{i'}(t) \mid m(t)] = m(t)C\ln(n)$ and is strictly decreasing for all points greater than $m(t)C\ln(n)$, Eq. (5) becomes:

$$
\begin{aligned}
Pr[Y_{i'}(t) \geq \kappa\ln(n) \mid m(t)] &= \sum_{j=\kappa\ln(n)}^{m(t)n} Pr[Y_{i'}(t) = j \mid m(t)]\\
&\leq m(t)n \cdot \left(\left(\frac{m(t)}{\kappa}\right)^{\kappa C} e^{C(\kappa-m(t))}\right)^{\ln(n)}\\
&= m(t)\left(\left(\frac{m(t)}{\kappa}\right)^{\kappa C} e^{(C(\kappa-m(t))+1)}\right)^{\ln(n)}.
\end{aligned}
$$

Since there are $\frac{n}{\ln(n)}$ bins, by linearity of expectation and by applying Markov's inequality, we conclude that the number $Z_\kappa(t)$ of bins with load at least $\kappa\ln(n)$, vanishes with high probability:

$$
\begin{aligned}
Pr[Z_\kappa(t) > 0 \mid m(t)] &\leq E[Z_\kappa(t) \mid m(t)]\\
&\leq \sum_{i=1}^{\rho} Pr[Y_i(t) \geq \kappa\ln(n) | \, m(t)]\\
&\leq \frac{n}{\ln(n)} Pr[Y_{i'}(t) \geq \kappa\ln(n) | \, m(t)]\\
&\leq \frac{n}{\ln(n)} m(t)\left(\left(\frac{m(t)}{\kappa}\right)^{\kappa C} e^{(C(\kappa-m(t))+1)}\right)^{\ln(n)}\\
&= \frac{m(t)}{\ln(n)}\left(\left(\frac{m(t)}{\kappa}\right)^{\kappa C} e^{(C(\kappa-m(t))+2)}\right)^{\ln(n)}.
\end{aligned}
$$

From the above inequality, in order to have $Pr[Z_\kappa(t) > 0 \mid m(t)] \leq E[Z_\kappa(t) \mid m(t)] \rightarrow 0$ it suffices to solve with respect to κ the following inequality:

$$
\left(\frac{m(t)}{\kappa}\right)^{\kappa C} e^{(C(\kappa-m(t))+2)} \leq 1 \Leftrightarrow \kappa \geq -\frac{Cm(t)-2}{C \cdot LW(-\frac{Cm(t)-2}{Cm(t)e})}.
$$

∎

6 Conclusions

In this paper we presented a new finger search tree with $O(1)$ worst-case update time and linear space that supports finger searching queries in $O(\log\log d)$ expected time with high probability when the insertions are μ-random, where μ is $(n/(\log\log n)^{1+\epsilon}, n^{1-\delta})$-smooth and the deletions are random. In general, we can support expected search and update times of $O(H(d))$ with high probability when the insertions are μ-random, where μ is $(n \cdot g(H(n)), H^{-1}(H(n)-1))$-smooth and g is a function satisfying $\sum_{i=1}^{\infty} g(i) = \Theta(1)$, and deletions are random. For several other restricted smooth densities, we can also achieve $o(\log\log d)$ expected search and update times with high probability. Our result is an improvement over the general searching problem considered in [1], since we can achieve better search bounds with high probability.

Since the techniques of Section 5 can reduce an arbitrary unknown distribution to an *almost* uniform distribution, it would be interesting to establish high probability search bounds for even larger classes than smooth distributions.

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