"Trees are the earth's endless effort to speak to the listening heaven."

– Rabindranath Tagore, Fireflies, 1928

Alice was walking beside the White Knight in Looking Glass Land.
"You are sad." the Knight said in an anxious tone: "let me sing you a song to comfort you."
"Is it very long?" Alice asked, for she had heard a good deal of poetry that day.
"It's long." said the Knight, "but it's very, very beautiful. Everybody that hears me sing it - either it brings tears to their eyes, or else -"
"Or else what?" said Alice, for the Knight had made a sudden pause.
"Or else it doesn't, you know. The name of the song is called 'Haddocks' Eyes.'"
"Oh, that's the name of the song, is it?" Alice said, trying to feel interested.
"No, you don't understand," the Knight said, looking a little vexed. "That's what the name is called. The name really is 'The Aged, Aged Man.'"
"Then I ought to have said 'That's what the song is called'?" Alice corrected herself.
"No you oughtn't: that's another thing. The song is called 'Ways and Means' but that's only what it's called, you know!"
"Well, what is the song then?" said Alice, who was by this time completely bewildered.
"I was coming to that," the Knight said. "The song really is 'A-sitting On a Gate': and the tune's my own invention."
So saying, he stopped his horse and let the reins fall on its neck: then slowly beating time with one hand, and with a faint smile lighting up his gentle, foolish face, he began...

– Lewis Carroll, Alice Through the Looking Glass, 1865

Lecture III
BALANCED SEARCH TREES

Anthropologists inform us that there is an unusually large number of Eskimo words for snow. The Computer Science equivalent of 'snow' is the 'tree' word: *(a,b)-tree, AVL tree, B-tree, binary search tree, BSP tree, conjugation tree, dynamic weighted tree, finger tree, half-balanced tree, heaps, interval tree, leftist tree, kd-tree, quadtree, octtree, optimal binary search tree, priority search tree, R-trees, randomized search tree, range tree, red-black tree, segment tree, splay tree, suffix tree, treaps, tries, weight-balanced tree, etc.* I have restricted the above list to trees which are used as search data structures. If we include trees arising in specific applications (e.g., Huffman tree, DFS/BFS tree, alpha-beta tree), we obtain an even more diverse list. The list can be enlarged to include variants of these trees: thus there are subspecies of B-trees called B^+- and B^*-trees, etc.

If there is a most important entry in the above list, it has to be binary search tree. It is the first non-trivial data structure that students encounter, after linear structures such as arrays, lists, stacks and queues. Trees are useful for implementing a variety of **abstract data types**. We shall see that all the common operations for search structures are easily implemented using binary search trees. Algorithms on binary search trees have a worst-case behavior that is proportional to the height of the tree. The height of a binary tree on n nodes is at least $\lfloor \lg n \rfloor$. We say that a family of binary trees is **balanced** if every tree in the family on n nodes has height $O(\log n)$. The implicit constant in the big-Oh notation here depends on the particular family. Such a family usually comes equipped with algorithms for inserting and deleting items from trees, while preserving membership in the family.

balance-ness is a family property

Many balanced families have been invented in computer science. They come in two basic forms: **height-balanced** and **weight-balanced schemes**. In the former, we ensure that the height of siblings are

"approximately the same". In the latter, we ensure that the number of descendants of sibling nodes are "approximately the same". Height-balanced schemes require us to maintain less information than the weight-balanced schemes, but the latter has some extra flexibility that are needed for some applications. The first balanced family was invented by the Russians Adel'son-Vel'skii and Landis in 1962, and are called **AVL trees**. We will describe several balanced families, including AVL trees and red-black trees. The notion of balance can be applied to non-binary trees; we will study the family of (a, b)**-trees** and generalizations. Tarjan [9] gives a brief history of some balancing schemes.

STUDY GUIDE: all our algorithms for search trees are described in such a way that they can be internalized, and we expect students to carry out hand-simulations on concrete examples. We do not provide any computer code, but once these algorithms are understood, it should be possible to implementing them in your favorite programming language.

§1. Search Structures with Keys

Search structures store a set of objects subject to searching and modification of these objects. Search structures can be viewed as a collection of **nodes** that are interconnected by pointers. Abstractly, they are just directed graphs with labels. Each node stores or represents an object which we call an **item**. We will be informal about how we manipulate nodes — they will variously look like ordinary variables and pointers[1] as in the programming language `C/C++`, or like references in `Java`. Let us look at some intuitive examples, relying on your prior knowledge about programming and variables.

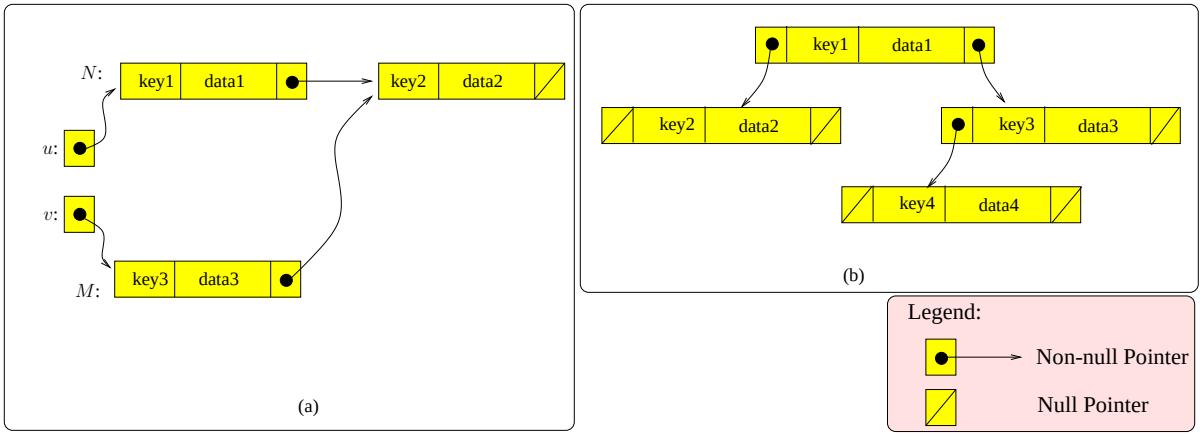


Figure 1: Two Kinds of Nodes: (a) linked lists, (b) binary trees

Each item is associated with a **key**. The rest of the information in an item is simply called **data**, so that we may view an item as the pair $(Key, Data)$. Besides an item, each node also stores one or more pointers to other nodes. Since the definition of a node includes (pointers) to other nodes, this is a recursive definition. Two simple types of nodes are illustrated in Figure 1: nodes with only one pointer (Figure 1(a)) are used to forming linked lists; nodes with two pointers can be used to form a binary trees (Figure 1(b)), or doubly-linked lists. Nodes with three pointers can be used in binary trees that require parent pointers. First, suppose N is a node variable of the type in Figure 1(a). Thus N has three **fields**, and we may name these fields as `key`, `data`, `next`. Each field has some data type. E.g. `key` is typically integer, `data` can be string, but it can almost anything, but `next` has to be a

[1] The concept of **locatives** introduced by Lewis and Denenberg [6] may also be used: a locative u is like a pointer variable in programming languages, but it has properties like an ordinary variable. Informally, u will act like an ordinary variable in situations where this is appropriate, and it will act like a pointer variable if the situation demands it. This is achieved by suitable automatic referencing and de-referencing semantics for such variables.

pointer to nodes. This field information constitutes the "type" of the node. To access these fields, we write N.`key`, N.`data` or N.`next`. The type of N.`next` is not that of a node, but pointer to a node. In our figures, we indicate the values of pointers by a directed arrow. Node pointer variables act rather like node variables: if variable u is a pointer to a node, we can also write u.`key`, u.`data` and u.`next` to access the fields in the node. There is a special pointer value called the **null pointer**, pointing to nothing. In Figure 1, null pointers are denoted by a special slash symbol.

There are at least three players here: the variables u, N and the node that both refer to. Compare this with the song 'A-sitting On a Gate' in the story of Alice and the White Knight

> Programming semantics: the difference between a node variable N and a node pointer variable u is best seen using the assignment operation. Let us assume that the node type is (`key`, `data`, `next`), M is another node variable and v another node pointer variable. In the assignment $N \leftarrow M$, we copy each of the three fields of M into the corresponding fields of N. But in the assignment $u \leftarrow v$, we simply make u point to the same node as v. Referring to Figure 1(a), we see that u is initially pointing to N, and v pointing to M. After the assignment $u \leftarrow v$, both pointers would now be pointing to M.

Examples of search structures:

(i) An *employee database* where each item is an employee record. The key of an employee record is the social security number, with associated data such as address, name, salary history, etc.

(ii) A *dictionary* where each item is a word entry. The key is the word itself, associated with data such as the pronunciation, part-of-speech, meaning, etc.

(iii) A *scheduling queue* in a computer operating systems where each item in the queue is a job that is waiting to be executed. The key is the priority of the job, which is an integer.

It is natural to refer such structures as **keyed search structures**. From an algorithmic point of view, the properties of the search structure are solely determined by the keys in items, the associated data playing no role. This is somewhat paradoxical since, for the users of the search structure, it is the data that is more important. With this caveat, we will normally ignore the data part of an item in our illustrations, thus *identifying the item with the key only*.

What is the point of searching for keys with no associated data?

Binary search trees is an example of a keyed search structure. Usually, each node of the binary search trees stores an item. In this case, our terminology of "nodes" for the location of items happily coincides with the concept of "tree nodes". However, there are versions of binary search trees whose items resides only in the leaves – the internal nodes only store keys for the purpose of searching.

Key values usually come from a totally ordered set. Typically, we use the set of integers for our ordered set. Another common choice for key values are character strings ordered by lexicographic ordering. For simplicity in these notes, the default assumption is that items have unique keys. When we speak of the "largest item", or "comparison of two items" we are referring to the item with the largest key, or comparison of the keys in two items, etc. Keys are called by different names to suggest their function in the structure. For example, a key may called a

In examples, keys $\equiv$ integers!

- **priority**, if there is an operation to select the "largest item" in the search structure (see example (iii) above);
- **identifier**, if the keys are unique (distinct items have different keys) and our operations use only equality tests on the keys, but not its ordering properties (see examples (i) and (ii));

- **cost** or **gain**, depending on whether we have an operation to find the minimum or maximum value;
- **weight**, if key values are non-negative.

More precisely, a **search structure** S is a representation of a set of items that supports the `lookUp` query. The lookup query, on a given key K and S, returns a node u in S such that the item in u has key K. If no such node exists, it returns $u = \mathsf{nil}$. Since S represents a set of items, two other basic operations we might want to do are inserting an item and deleting an item. If S is subject to both insertions and deletions, we call S a **dynamic set** since its members are evolving over time. In case insertions, but not deletions, are supported, we call S a **semi-dynamic set**. In case both insertion and deletion are not allowed, we call S a **static set**. The dictionary example (ii) above is a static set from the viewpoint of users, but it is a dynamic set from the viewpoint of the lexicographer.

Two search structures that store exactly the same set of items are said to be **equivalent**. An operation that preserves the equivalence class of a search structure is called an **equivalence transformation**.

§2. Abstract Data Types

This section contains a general discussion on abstract data types (ADT's). It may be used as a reference; a light reading is recommended for the first time

Students may be unfamiliar with the term **abstract data type** (ADT) but it is intuitively the same concept as an **interface** in the `Java` language. Again using the terminology of modern object-oriented languages `C++` or `Java`, we view a search data structure is an instance of a **container class**. Each instance stores a set of items and have a well-defined set of **members** (i.e., variables) and **methods** (i.e., operations). Thus, a binary tree is just an instance of the "binary tree class". The "methods" of such class support some subset of the following operations listed below.

Java fans: ADT = interface

¶1. ADT Operations. We will now list all the main operations found in all the ADT's that we will study. *We emphasize that each ADT will only require a proper subset of these operations. The full set of ADT operations listed here is useful mainly as a reference.* We will organize these operations into four groups (I)-(IV):

(I) Initializer and Destroyers	`make`()→*Structure*, `kill`()
(II) Enumeration and Order	`list`() →*Node*, `succ`(*Node*)→*Node*, `pred`(*Node*)→*Node*, `min`()→*Node*, `max`()→*Node*,
(III) Dictionary-like Operations	`lookUp`(*Key*)→*Node*, `insert`(*Item*)→*Node*, `delete`(*Node*), `deleteMin`()→*Item*,
(IV) Set Operations	`split`(*Key*)→ *Structure*, `merge`(*Structure*).

Most applications do not need the full suite of the these operations. Below, we will choose various subsets of this list to describe some well-known ADT's. The meaning of these operations are fairly intuitive. We will briefly explain them. Let S, S' be search structures, viewed as instances of a suitable class. Let K be a key and u a node. Each of the above operations are invoked from some S: thus, S.`make`() will initialize the structure S, and S.`max`() returns the maximum value in S.

When there is only one structure S, we may suppress the reference to S. E.g., S.`merge`(S') can be simply written as "`merge`(S')".

Group (I): We need to initialize and dispose of search structures. Thus `make` (with no arguments) returns a brand new empty instance of the structure. The inverse of `make` is `kill`, to remove a structure. These are constant time operations.

Group (II): This group of operations are based on some linear ordering of the items stored in the data structure. The operation `list`() returns a node that is an iterator. This iterator is the beginning of a list that contains all the items in S in *some arbitrary* order. The ordering of keys is not used by the iterators. The remaining operations in this group depend on the ordering properties of keys. The `min`() and `max`() operations are obvious. The successor `succ`(u) (resp., predecessor `pred`(u)) of a node u refers to the node in S whose key has the next larger (resp., smaller) value. This is undefined if u has the largest (resp., smallest) value in S.

Note that `list`() can be implemented using `min`() and `succ`(u) or `max`() and `pred`(u). Such a listing has the additional property of sorting the output by key value.

Group (III): The first three operations of this group,

$$\texttt{lookUp}(K) \to u, \quad \texttt{insert}(K, D) \to u, \quad \texttt{delete}(u),$$

constitute the "dictionary operations". In many ADT's, these are the central operations.

The node u returned by `lookUp`(K) has the property that u.`key` $= K$. In conventional programming languages such as `C`, nodes are usually represented by pointers. In this case, the `nil` pointer is returned by the `lookUp` function when there is no item in S with key K. When we perform S.`lookUp`(K), the structure S itself may be modified to another equivalent structure.

In case no such item exists, or it is not unique, some convention should be established. At this level, we purposely leave this under-specified. Each application should further clarify this point. For instance, in case the keys are not unique, we may require that `lookUp`(K) returns an iterator that represents the entire set of items with key equal to K.

Both `insert` and `delete` have the obvious basic meaning. In some applications, we may prefer to have deletions that are based on key values. But such a deletion operation can be implemented as '`delete`(`lookUp`(K))'. In case `lookUp`(K) returns an iterator, we would expect the deletion to be performed over the iterator.

The fourth operation S.`deleteMin`() in Group (III) is not considered a dictionary operation. The operation returns the minimum item I in S, and simultaneously deletes it from S. Hence, it could be implemented as `delete`(`min`()). But because of its importance, `deleteMin`() is often directly implemented using special efficient techniques. In most data structures, we can replace `deleteMin` by `deleteMax` without trouble. However, this is not the same as being able to support both `deleteMin` and `deleteMax` simultaneously.

Group (IV): The final group of operations,

$$S.\texttt{split}(K) \to S', \quad S.Merge(S'),$$

represent manipulation of entire search structures, S and S'. If $S.\texttt{split}(K) \to S'$ then all the items in S with keys greater than K are moved into a new structure S'; the remaining items are retained in S. Conversely, the operation $S.\texttt{merge}(S')$ moves all the items in S' into S, and S' itself becomes empty. This operation assumes that all the keys in S are less than all the items in S'. Thus `split` and `merge` are inverses of each other.

¶2. Implementation of ADTs using Linked Lists. The basic premise of ADTs is that we should separate specification (given by the ADT) from implementation. We have just given the specifications, so let us now discuss a concrete implementation.

Data structures such as arrays, linked list or binary search trees are called **concrete data types**. Hence ADTs are to be implemented by such concrete data types. We will now discuss a simple implementation of all the ADT operations using linked lists. This humble data structure comes in 8 varieties according to Tarjan [9]. For concreteness, we use the variety that Tarjan calls **endogeneous doubly-linked list**. Endogeneous means the item is stored in the node itself: thus from a node u, we can directly access $u.\texttt{key}$ and $u.\texttt{data}$. Doubly-linked means u has two pointers $u.\texttt{next}$ and $u.\texttt{prev}$. These two pointers satisfies the invariant $u.\texttt{next} = v$ iff $v.\texttt{prev} = u$. We assume students understand linked lists, so the following discussion is partly a review of linked lists.

You know this!

Let L be a such a linked list. Conceptually, a linked list is set of nodes organized in some linear order. The linked list has two special nodes, $L.\texttt{head}$ and $L.\texttt{tail}$, corresponding to the first and last node in this linear order. We can visit all the nodes in L using the following routine with a simple while-loop:

```
LISTTRAVERSAL(L)
    u ← L.head
    while (u ≠ nil)
        [VISIT(u)]
        u ← u.next
    [CLEANUP()]
```

List traversal shell

Here, VISIT(u) and CLEANUP() are subroutine or more accurately "macros" that depend on the application. As a default, they do nothing ("no-op"). We call LISTTRAVERSAL a shell program; this theme will be taken up more fully when we discuss tree traversal below (§4). Since the while-loop (by hypothesis) visits every node in L, there is a unique node u (assume L is non-empty) with $u.\texttt{next} = \text{nil}$. This node is $L.\texttt{tail}$.

In programming, macros are a mechanism for textual substitution into the code

It should be obvious how to implement most of the ADT operations using linked lists. We ask the student to carry this out for the operations in Groups (I) and (II). Here we focus on the dictionary operations:

- `lookUp`(K): We can use the above ListTraversal routine but replace "VISIT(u)" by the following code fragment:

$$\boxed{\text{VISIT}(u)} \equiv \text{if } (u.\texttt{key} = K) \text{ Return}(u)$$

Note that since VISIT is a macro, the Return in VISIT is a not return from VISIT, but from the `lookUp` routine! The CLEANUP() statement is similarly replaced by

```
CLEANUP() ≡ Return(nil)
```

The correctness of this implementation should be obvious.

- `insert`(K, D): We use the ListTraversal shell, but define VISIT(u) as the following macro:

```
VISIT(u):   if (u.key = K) Return(nil)
```

Thus, if the key K is found in u, we return nil, indicating failure (duplicate key). The CLEANUP() macro is:

```
CLEANUP():
    u ← new(Node)
    u.key := K; u.data := D
    u.next := L.head
    L.head := u
    Return(u)
```

where $new(Node)$ returns a pointer to space on the heap for a node.

- `delete`(u): Since u is a pointer to the node to be deleted, this amounts to the standard deletion of a node from a doubly-linked list:

```
    u.next.prev ← u.prev
    u.prev.next ← u.next
    del(u)
```

where $del(u)$ is a standard routine to return a memory to the system heap. This takes time $O(1)$

¶3. Complexity Analysis. Another simple way to implement our ADT operations is to use arrays (Exercise). In subsequent sections, we will discuss how to implement the ADT operations using balanced binary trees. In order to understand the tradeoffs in these alternative implementations, we now provide a complexity analysis of each implementation. Let us do this for our linked list implementation.

We can provide a worst case time complexity analysis. For this, we need to have a notion of input size: this will be n, the number of nodes in the (current) linked list. Consistent with our principles in Lecture I, we will perform a Θ-order analysis.

The complexity of `lookUp`(K) is $\Theta(n)$ in the worst case because we have to traverse the entire list in the worst case. Both `insert`(K, D) and `delete`(u) are preceded by `lookUp`'s, which we know takes $\Theta(n)$ in the worst case. The `delete` operation is $\Theta(1)$. Note that such an efficient deletion is possible because we use doubly-linked lists; with singly-linked lists, we need $\Theta(n)$ time.

More generally, with linked list implementation, all the ADT operations can easily be shown to have time complexity either $\Theta(1)$ or $\Theta(n)$. The principal goal of this chapter is to show that the $\Theta(n)$ can be replaced by $\Theta(\log n)$. This represents an "exponential speedup" from the linked list implementation.

¶4. Some Abstract Data Types. The above operations are defined on typed domains (keys, structures, items) with associated semantics. An **abstract data type** (acronym "ADT") is specified by

- one or more "typed" domains of objects (such as integers, multisets, graphs);
- a set of operations on these objects (such as lookup an item, insert an item);
- properties (axioms) satisfied by these operations.

These data types are "abstract" because we make no assumption about the actual implementation.

It is not practical or necessary to implement a single data structure that has all the operations listed above. Instead, we find that certain subset of these operations work together nicely to solve certain problems. Computer science has discovered that following subset of operations to be widely applicable:

- **Dictionary ADT**: `lookUp`, [`insert`, [`delete`]].
- **Ordered Dictionary ADT**: `lookUp`, `insert`, `delete`, `succ`, `pred`.
- **Priority queue ADT**: `deleteMin`, `insert`, [+`delete`, [+`decreaseKey`]].
- **Fully mergeable dictionary ADT**: `lookUp`, `insert`, `delete`, `merge`, `split`.

In some stripped-down versions of these ADT, operations within $[\cdots]$ may be omitted. For instance, a dictionary ADT without `delete` is called a **semi-dynamic dictionary**, and if it also omits `insert`, it is called a **static dictionary**. Note that the latter only has one operation, `lookUp`.

Alternatively, some ADT's can be enhanced by additional operations. For instance, a priority queue ADT traditionally supports only `deleteMin` and `insert`. But in some applications, it must be enhanced with the operation of `delete` and/or `decreaseKey`. The latter operation can be defined as

$$\texttt{decreaseKey}(K, K') \equiv [u \leftarrow \texttt{lookUp}(K); \texttt{delete}(u); \texttt{insert}(K', u.\texttt{data})]$$

with the extra condition that $K' < K$ (assuming a min-queue). In other words, we change the priority of the item u in the queue from K to K'. Since $K' < K$, this amounts to increasing its priority of u in a min-queue.

If the deletion in dictionaries are based on keys (see comment above) then we may think of a dictionary as a kind of **associative memory**. If we omit the `split` operation in fully mergeable dictionary, then we obtain the **mergeable dictionary** ADT. The operations `make` and `kill` (from group (I)) are assumed to be present in every ADT.

NOTES:
1. Variant interpretations of all these operations are possible. For instance, some version of `insert` may wish to return a boolean (to indicate success or failure) or not to return any result (in case the application will never have an insertion failure).
2. Other useful functions can be derived from the above. E.g., it is useful to be able to create a structure S containing just a single item I. This can be reduced to 'S.`make`(); S.`insert`(I)'.
3. The concept of ADT was a major research topic in the 1980's. Many of these ideas found their way into structured programming languages such as Pascal and their modern successors. An interface in Java is a kind of ADT where we capture only the types of operation. Our discussion of ADT is informal, but one way to study them formally is to describe axioms that these operations satisfy. For instance, if S is a stack, then we can postulate the axiom that pushing an item x on S followed by popping S should return the item x. In our treatment, we relied on informal understanding of these ADT's to avoid the axiomatic treatment.

EXERCISES

Exercise 2.1: Consider the dictionary ADT.

(a) Describe algorithms to implement this ADT when the concrete data structures are arrays.

NOTE: An interesting difference from implementation using linked lists is to decide what to do when the array is full. We want you to allocate space for a bigger array (how would you choose its size?). Furthermore, what is the analogue of the ListTraversal Shell?

(b) Analyze the complexity of your algorithms in (a). Compare this complexity with that of the linked list implementation. ♢

Exercise 2.2: Repeat the previous question for the priority queue ADT. ♢

Exercise 2.3: Suppose D is a dictionary with the dictionary operations of lookup, insert and delete. List a complete set of axioms (properties) for these operations. ♢

END EXERCISES

§3. Binary Search Trees

We introduce binary search trees and show that such trees can support all the operations described in the previous section on ADT. Our approach will be somewhat unconventional, because we want to reduce all these operations to the single operation of "rotation".

the universal operation!

Recall the definition and basic properties of binary trees in the Appendix of Chapter I. Figure 2 shows two binary trees (small and big) which we will use in our illustrations. For each node u of the tree, we store a value $u.\texttt{key}$ called its key. The keys in Figure 2 are integers, used simply as identifiers for the nodes.

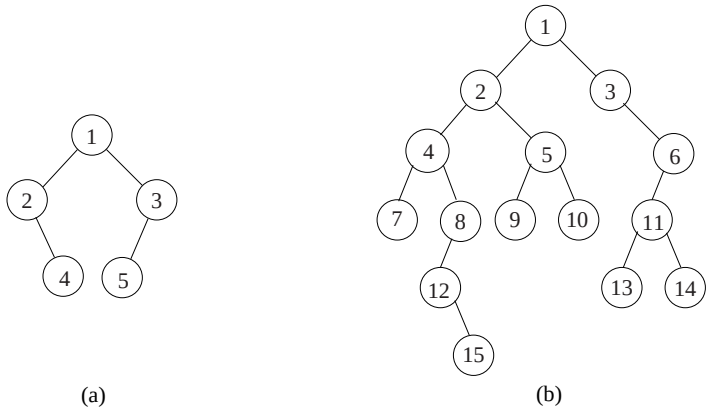
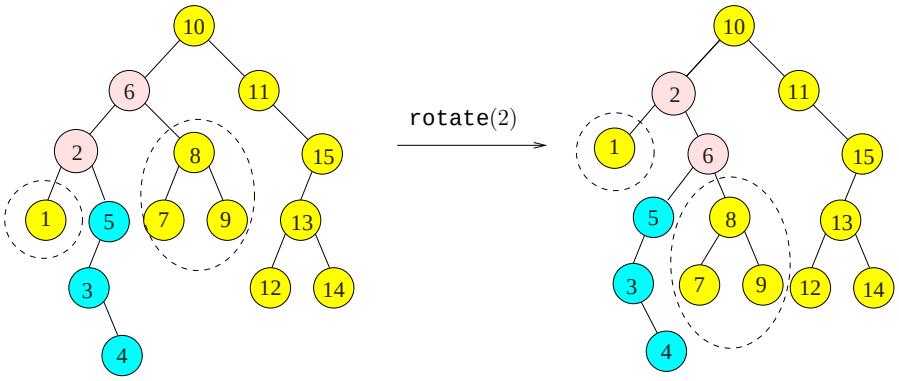


Figure 2: Two binary (not search) trees: (a) small, (b) big

Briefly, a binary tree T is a set $N \geq 0$ of nodes that is either the empty set, or N has a node u called the root. In Figure 2, $N = \{1, 2, 3, 4, 5\}$ for the small tree and $N = \{1, 2, 3, \ldots, 15\}$ for the big tree.

The remaining nodes $N \setminus \{u\}$ are partitioned into two sets of nodes that recursively form binary trees, T_L and T_R. If T_L (resp., T_R) is non-empty, then its root is called the left (resp., right) child of u. This definition of binary trees is based on **structural induction**. The **size** of T is $|N|$, and is denoted $|T|$; also T_L, T_R are the **left** and **right subtrees** of T.



(a) (b)

Figure 3: (a) Binary Search Tree on keys $\{1, 2, 3, 4, \ldots, 14, 15\}$. (b) After `rotate`$(2)$.

The keys of the binary trees in Figure 2 are just used as identifiers. To turn binary trees into a binary *search* tree, we must organize the keys in a particular way. Such a binary search tree is illustrated in Figure 3(a). structurally, it is the big binary tree in Figure 2, but now the keys are no longer just arbitrary identifiers.

A binary tree T is called **binary search tree** (BST) the key $u.\texttt{key}$ at each node u satisfies the **binary search tree property**:

$$u_L.\texttt{key} < u.\texttt{key} \leq u_R.\texttt{key}. \tag{1}$$

where u_L and u_R are (resp.) any **left descendant** and **right descendant** of u. Please verify that the binary search in of Figure 3 obeys (1) at each node u.

The "standard mistake" is to replace (1) by $u.\texttt{left.key} < u.\texttt{key} \leq u.\texttt{right.key}$. By definition, a left (right) descendant of u is a node in the subtree rooted at the left (right) child of u. The left and right children of u are denoted by $u.\texttt{left}$ and $u.\texttt{right}$. The standard mistake focuses on a necessary, but not sufficient, condition in the concept of a BST. Self-check: construct a counter example to the standard mistake using a binary tree with 4 nodes (actually 3 nodes suffice). good test question...

> Fundamental Rule about binary trees: *most properties about binary trees are best proved by induction on the structure of the tree. Likewise, algorithms for binary trees are often best described using structural induction.*

¶5. Lookup. The algorithm for key lookup in a binary search tree is almost immediate from the binary search tree property: to look for a key K, we begin at the root (remember the good point above?). In general, suppose we are looking for K in some subtree rooted at node u. If $u.\texttt{key} = K$, we are done. Otherwise, either $K < u.\texttt{key}$ or $K > u.\texttt{key}$. In the former case, we recursively search the left subtree of u; otherwise, we recurse in the right subtree of u. In the presence of duplicate keys, what does lookup return? There are two interpretations: (1) We can return the first node u we find that has the given key K. (2) We may insist that we continue to explicitly locate all the other keys.

In any case, requirement (2) can be regarded as an extension of (1), namely, given a node u, find all the other nodes below u with same same key as $u.\texttt{key}$. This can be solved separately. Hence we may assume interpretation (1) in the following.

¶6. Insertion. To insert an item with key K, we proceed as in the Lookup algorithm. If we find K in the tree, then the insertion fails (assuming distinct keys). Otherwise, we reach a leaf node u. Then the item can be inserted as the left child of u if $u.\texttt{key} > K$, and otherwise it can be inserted as the right child of u. In any case, the inserted item is a new leaf of the tree.

¶7. Rotation. This is not a listed operation in §2. It is an equivalence operation, i.e., it transforms a binary search tree into another one with exactly the same set of keys. By itself, rotation does not appear to do anything useful. Remarkably, we shall show that rotation can[2] form the basis for all other binary tree operations.

The operation $\texttt{rotate}(u)$ is a null operation ("no-op" or identity transformation) when u is a root. So assume u is a non-root node in a binary search tree T. Then $\texttt{rotate}(u)$ amounts to the following transformation of T (see figure 4).

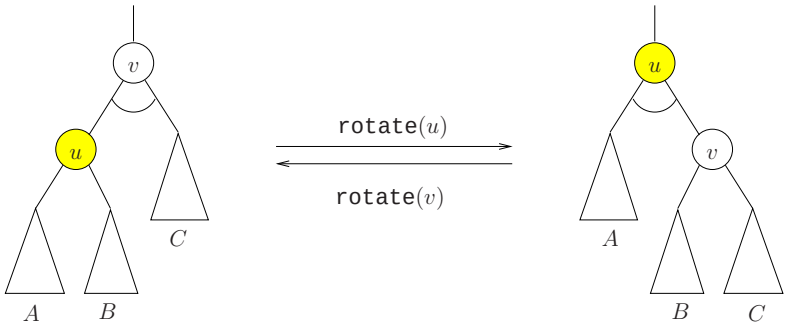


Figure 4: Rotation at u and its inverse.

In $\texttt{rotate}(u)$, we basically want to invert the parent-child relation between u and its parent v. The other transformations are more or less automatic, given that the result is to remain a binary search tree. If the subtrees A, B, C (any of these can be empty) are as shown in figure 4, then they must re-attach as shown. This is the only way to reattach as children of u and v, since we know that

$$A < u < B < v < C$$

in the sense that each key in A is less than u which is less than any key in B, etc. Actually, only the parent of the root of B has switched from u to v. Notice that after $\texttt{rotate}(u)$, the former parent of v (not shown) will now have u instead of v as a child. Clearly the inverse of $\texttt{rotate}(u)$ is $\texttt{rotate}(v)$. The explicit pointer manipulations for a rotation are left as an exercise. After a rotation at u, the depth of u is decreased by 1. Note that $\texttt{rotate}(u)$ followed by $\texttt{rotate}(v)$ is the identity[3] operation, as illustrated in figure 4.

Recall that two search structures are equivalent if they contain the same set of items. Clearly, rotation is an equivalence transformation.

[2] Augmented by natural operations such as adding or removing a node.
[3] Also known as null operation or no-op

¶8. Graphical convention: Figure 4 encodes two conventions: consider the figure on the left side of the arrow (the same convention hold for the figure on the right side). First, the edge connecting v to its parent is directed vertically upwards. This indicates that v can be the left- or right-child of its parent. Second, the two edges from v to its children are connected by a circular arc. This is to indicate that u and its sibling could exchange places (i.e., u could be the right-child of v even though we choose to show u as the left-child). Thus Figure 4 is a compact way to represent four distinct situations.

¶9. Implementation of rotation. Let us discuss how to implement rotation. Until now, when we draw binary trees, we only display child pointers. But we must now explicitly discuss parent pointers.

Let us classify a node u into one of three **types**: *left*, *right* or *root*. This is defined in the obvious way. E.g., u is a left type iff it is not a root and is a left child. The type of u is easily tested: u is type root iff $u.\texttt{parent} = \mathsf{nil}$, and u is type left iff $u.\texttt{parent.left} = u$. Clearly, $\texttt{rotate}(u)$ is sensitive to the type of u. In particular, if u is a root then $\texttt{rotate}(u)$ is the null operation. If $T \in \{\texttt{left}, \texttt{right}\}$ denote left or right type, its **complementary type** is denoted $\overline{T}$, where $\overline{\texttt{left}} = \texttt{right}$ and $\overline{\texttt{right}} = \texttt{left}$.

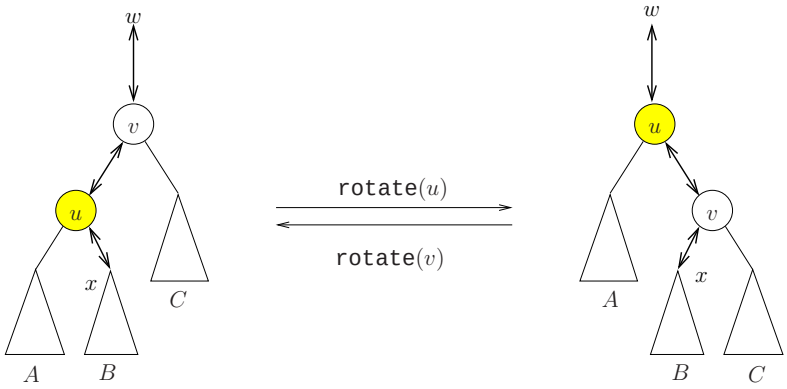


Figure 5: Links that must be fixed in $\texttt{rotate}(u)$.

We are ready to discuss the function $\texttt{rotate}(u)$, which we assume will return the node u. Assume u is not the root, and its type is $T \in \{\texttt{left}, \texttt{right}\}$. Let $v = u.\texttt{parent}$, $w = v.\texttt{parent}$ and $x = v.\overline{T}$. Note that w and x might be nil. Thus we have potentially three child-parent pairs:

$$(x, u), (u, v), (v, w). \tag{2}$$

But after rotation, we will have the transformed child-parent pairs:

$$(x, v), (v, u), (u, w). \tag{3}$$

These pairs are illustrated in Figure 5 where we have explicitly indicated the parent pointers as well as child pointers. Thus, to implement rotation, we need to reassign 6 pointers (3 parent pointers and 3 child pointers). We show that it is possible to achieve this re-assignment using exactly 6 assignments.

Figure 6: Simplified view of $\texttt{rotate}(u)$ as fixing a doubly-linked list (x, u, v, w).

Such re-assignments must be done in the correct order. It is best to see what is needed by thinking of (2) as a doubly-linked list (x, u, v, w) which must be converted into the doubly-linked list (x, v, u, w) in (3). This is illustrated in Figure 6. For simplicity, we use the terminology of doubly-linked list so that u.`next` and u.`prev` are the forward and backward pointers of a doubly-linked list. Here is[4] the code:

ROTATE(u):
- ▷ *Fix the forward pointers*
  1. u.`prev.next` $\leftarrow u$.`next`
     ◁ x.`next` $= v$
  2. u.`next` $\leftarrow u$.`next.next`
     ◁ u.`next` $= w$
  3. u.`prev.next.next` $\leftarrow u$
     ◁ v.`next` $= u$
- ▷ *Fix the backward pointers*
  4. u.`next.prev.prev` $\leftarrow u$.`prev`
     ◁ v.`prev` $= x$
  5. u.`next.prev` $\leftarrow u$
     ◁ w.`prev` $= u$
  6. u.`prev` $\leftarrow u$.`prev.next`
     ◁ u.`prev` $= v$

We can now translate this sequence of 6 assignments into the corresponding assignments for binary trees: the u.`next` pointer may be identified with u.`parent` pointer. However, u.`prev` would be $u.T$ where $T \in \{\texttt{left}, \texttt{right}\}$ is the type of x. Moreover, v.`prev` is $v.\overline{T}$. Also w.`prev` is $w.T'$ for another type T'. A further complication is that x or/and w may not exist; so these conditions must be tested for, and appropriate modifications taken.

If we use temporary variables in doing rotation, the code can be simplified (Exercise).

¶10. Variations on Rotation. The above rotation algorithm assumes that for any node u, we can access its parent. This is true if each node has a parent pointer u.`parent`. *This is our default assumption for binary trees.* In case this assumption fails, we can replace rotation with a pair of variants: called **left-rotation** and **right-rotation**. These can be defined as follows:

$$\texttt{left-rotate}(u) \equiv \texttt{rotate}(u.\texttt{left}), \qquad \texttt{right-rotate}(u) \equiv \texttt{rotate}(u.\texttt{right}).$$

It is not hard to modify all our rotation-based algorithms to use the left- and right-rotation formulation if we do not have parent pointers. Of course, the corresponding code would be twice as fast since we have halved the number of pointers to manipulate.

¶11. Double Rotation. Suppose u has a parent v and a grandparent w. Then two successive rotations on u will ensure that v and w are descendants of u. We may denote this operation by $\texttt{rotate}^2(u)$. Up to left-right symmetry, there are two distinct outcomes in $\texttt{rotate}^2(u)$: (i) either v, w are becomes children of u, or (ii) only w becomes a child of u and v a grandchild of u. These depend on whether u is the **outer** or **inner** grandchildren of w. These two cases are illustrated in Figure 7. [As an exercise, we ask the reader to draw the intermediate tree after the first application of $\texttt{rotate}(u)$ in this figure.]

[4] In Lines 3 and 5, we used the node u as a pointer on the right hand side of an assignment statement. Strictly speaking, we ought to take the address of u before assignment. Alternatively, think of u as a "locator variable" which is basically a pointer variable with automatic ability to de-reference into a node when necessary.

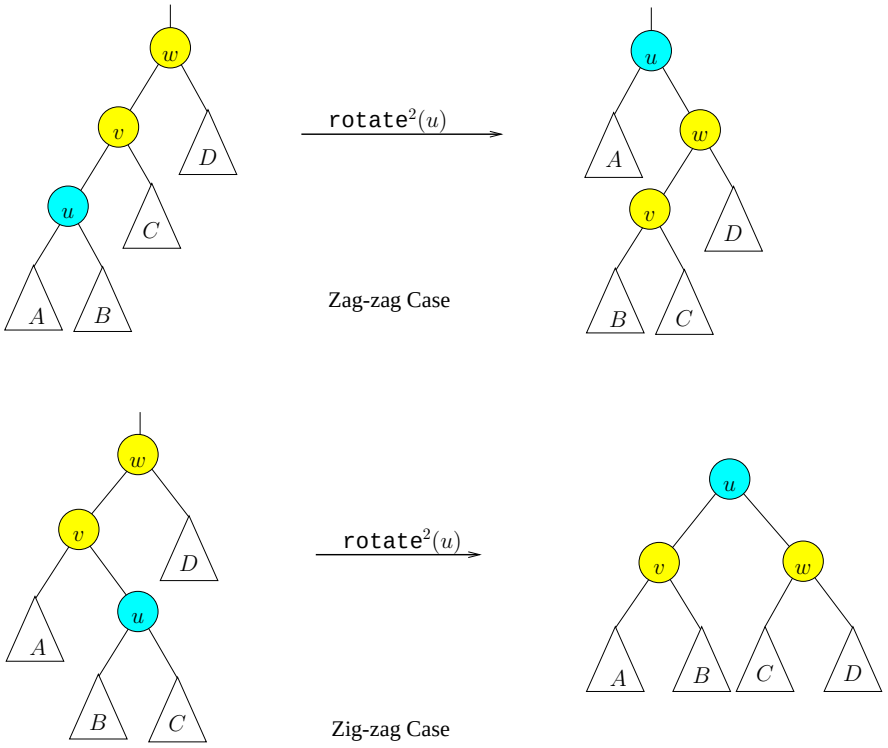


Figure 7: Two outcomes of $\texttt{rotate}^2(u)$

It turns out that case (ii) is the more important case. For many purposes, we would like to view the two rotations in this case as one indivisible operation: hence we introduce the term **double rotation** to refer to case (ii) only. For emphasis, we might call the original rotation a **single rotation**.

These two cases are also known as the zig-zig (or zag-zag) and zig-zag (or zag-zig) cases, respectively. This terminology comes from viewing a left turn as zig, and a right turn as zag, as we move from up a root path. The Exercise considers how we might implement a double rotation more efficiently than by simply doing two single rotations.

¶12. Root path, Extremal paths and Spines. A path is a sequence of nodes $(u_0, u_1, \ldots, u_n)$ where u_{i+1} is a child of u_i. The length of this path is n, and u_n is also called the **tip** of the path. E.g., $(2, 4, 8, 12)$ is a path in Figure 2(b), with tip 12.

Relative to a node u, we now introduce 5 paths that originates from u. The first is the path from u to the root, called the **root path** of u. In figures, the root path is displayed as an upward path, following parent pointers from the node u. E.g., if $u = 4$ in Figure 2(b), then the root path is $(4, 2, 1)$. Next we introduce 4 downward paths from u. The **left-path** of u is simply the path that starts from u and keeps moving towards the left or right child until we cannot proceed further. The **right-path** of u is similarly defined. E.g., with u as before, the left-path is $(4, 7)$ and right-path is $(4, 8)$. Collectively, we refer to the left- and right-paths as **extremal paths**. Next, we define the **left-spine** of a node u is defined to be the path $(u, \text{rightpath}(u.\texttt{left}))$. In case $u.\texttt{left} = \textsf{nil}$, the left spine is just the trivial path (u) of length 0. The **right-spine** is similarly defined. E.g., with u as before, the left-spine is $(4, 7)$ and right-spine is $(4, 8, 12)$. The tips of the left- and right-paths at u correspond to the minimum and maximum keys in the subtree at u. The tips of the left- and right-spines, provided they are different from u itself, correspond

to the predecessor and successor of u. Clearly, u is a leaf iff all these four tips are identical and equal to u.

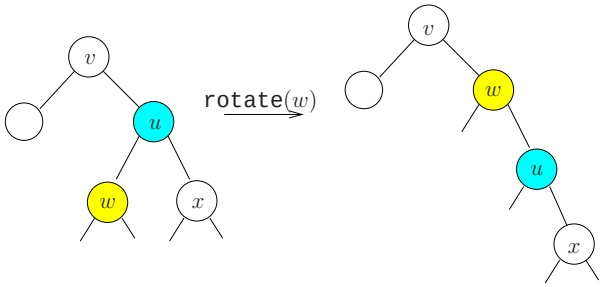


Figure 8: Reduction of the left-spine of u after $\texttt{rotate}(u.\texttt{left}) = \texttt{rotate}(w)$.

After performing a left-rotation at u, we reduce the left-spine length of u by one (but the right-spine of u is unchanged). See Figure 8. More generally:

LEMMA 1. *Let $(u_0, u_1, \ldots, u_k)$ be the left-spine of u and $k \geq 1$. Also let $(v_0, \ldots, v_m)$ be the root path of u, where v_0 is the root of the tree and $u = v_m$. After performing $\texttt{rotate}(u.\texttt{left})$,*
(i) the left-spine of u becomes $(u_0, u_2, \ldots, u_k)$ of length $k - 1$,
(ii) the right-spine of u is unchanged, and
(iii) the root path of u becomes $(v_0, \ldots, v_m, u_1)$ of length $m + 1$.

In other words, after a left-rotation at u, the left child of u transfers from the left-spine of u to the root path of u. Similar remarks apply to right-rotations. If we repeatedly do left-rotations at u, we will reduce the left-spine of u to length 0. We may also alternately perform left-rotates and right-rotates at u until one of its 2 spines have length 0.

¶13. Deletion. Suppose we want to delete a node u. In case u has at most one child, this is easy to do – simply redirect the parent's pointer to u into the unique child of u (or nil if u is a leaf). Call this procedure $Cut(u)$. It is now easy to describe a general algorithm for deleting a node u:

```
DELETE(T, u):
Input:   u is node to be deleted from T.
Output:  T, the tree with u deleted.
    while u.left ≠ nil do
        rotate(u.left).
    Cut(u)
```

If we maintain information about the left and right spine heights of nodes (Exercise), and the right spine of u is shorter than the left spine, we can also perform the while-loop by going down the right spine instead. The overall effect of this algorithm is schematically illustrated in Figure 9.

We ask the reader to simulate the operations of $Delete(T, 10)$ where T is the BST of Figure 3.

¶14. Standard Deletion Algorithm. The preceding deletion algorithm is simple but is actually quite non-standard. We now describe the **standard deletion algorithm**:

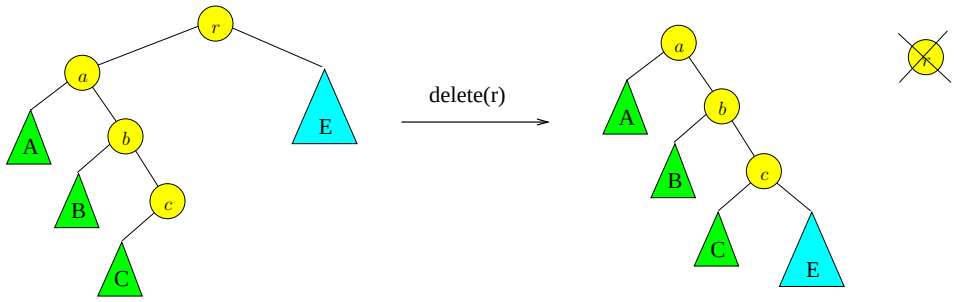


Figure 9: Deletion based on rotation.

DELETE(T, u):
Input: u is node to be deleted from T.
Output: T, the tree with item in u deleted.
if u has at most one child, apply Cut(u) and return.
else let v be the tip of the right spine of u.
Move the item in v into u (effectively removing the item in u)
Cut(v).

Note that in the else-case, the node u is not physically removed: only the item represented by u is removed. Again, the node v that is physically removed (i.e., cut) has at most one child. If we have to return a value, it is useful to return the parent of the node v that was cut – this will be used in rebalancing tree (see AVL deletion below).

Again, the reader should simulate the operations of $Delete(T, 10)$, using this standard algorithm, and compare the results to the rotation-based algorithm.

The rotation-based deletion is conceptually simpler, and will be useful for amortized algorithms later. However, the rotation-based algorithm seems to be slower as it requires an unbounded number of pointer assignments.

¶15. Inorder listing of a binary tree.

LEMMA 2. *Let T be a binary tree on n nodes. There is a unique way to assign the keys $\{1, 2, \ldots, n\}$ to the nodes of T such that the resulting tree is a binary search tree on these keys.*

We leave the simple proof to an Exercise. For example, if T is the binary tree in Figure 2(b), then this lemma would assign the keys $\{1, \ldots, 15\}$ to the nodes of T as in Figure 3(a).

For each $i = 1, \ldots, n$, we may refer to node $u \in T$ as the i**th node** if Lemma 2 assigns the key i to u. In particular, we can speak of the **first** and **last node** of T. The unique enumeration of the nodes of T from first to last is called the **in-order listing** of T.

¶16. Successor and Predecessor. If u is the ith node of a binary tree T, the **successor** of u refers to the $(i+1)$st node of T. By definition, u is the **predecessor** of v iff v is the successor of u. Let $\texttt{succ}(u)$ and $\texttt{pred}(u)$ denotes the successor and predecessor of u. Of course, $\texttt{succ}(u)$ (resp., $\texttt{pred}(u)$) is undefined if u is the last (resp., first) node in the in-order listing of the tree.

We will define a closely related concept, but applied to any key K. Let K be a key, not necessarily occurring in T. Define the **successor** of K in T to be the least key K' in T such that $K < K'$. We similarly define the **predecessor** of K in T to be the greatest K' in T such that $K' < K$.

In some applications of binary trees, we want to maintain pointers to the successor and predecessor of each node. In this case, these pointers may be denoted $u.\texttt{succ}$ and $u.\texttt{pred}$. Note that the successor/predecessor pointers of nodes is unaffected by rotations. *Our default version of binary trees do not include such pointers.*

Let us make some simple observations:

LEMMA 3. *Let u be a node in a binary tree, but u is not the last node in the in-order traversal of the tree.*
(i) $u.\texttt{right} = \text{nil}$ iff u is the tip of the left-spine of some node v. Moreover, such a node v is uniquely determined by u.
(ii) If $u.\texttt{right} = \text{nil}$ and u is the tip of the left-spine of v, then $\texttt{succ}(u) = v$.
(iii) If $u.\texttt{right} \neq \text{nil}$ then $\texttt{succ}(u)$ is the tip of the right-spine of u.

It is easy to derive an algorithm for $\texttt{succ}(u)$ using the above observation.

```
SUCC(u):
    1.   if u.right ≠ nil   ◁ return the tip of the right-spine of u
    1.1      v ← u.right;
    1.2      while v.left ≠ nil, v ← v.left;
    1.3      Return(v).
    2.   else   ◁ return v where u is the tip of the left-spine of v
    2.1      v ← u.parent;
    2.2      while v ≠ nil and u = v.right,
    2.3           (u, v) ← (v, v.parent).
    2.4      Return(v).
```

Note that if $\texttt{succ}(u) = \text{nil}$ then u is the last node in the in-order traversal of the tree (so u has no successor). The algorithm for $\texttt{pred}(u)$ is similar.

¶17. Min, Max, DeleteMin. This is trivial once we notice that the minimum (maximum) item is in the first (last) node of the binary tree. Moreover, the first (last) node is at the tip of the left-path (right-path) of the root.

¶18. Merge. To merge two trees T, T' where all the keys in T are less than all the keys in T', we proceed as follows. Introduce a new node u and form the tree rooted at u, with left subtree T and right subtree T'. Then we repeatedly perform left rotations at u until $u.\texttt{left} = \text{nil}$. At this point, we can already delete u (even though $u.\texttt{right}$ may not be nil).

However, if you like, you can perform right rotations at u until $u.\texttt{right} = \text{nil}$. Now u is a leaf and can be deleted. In either case, the result is the merge of T and T'.

¶19. Split. Suppose we want to split a tree T at a key K. Recall the semantics of split from §2: $T.split(K) \to T'$. This says that all the keys less than or equal to K is retained in T, and the rest are

split off into a new tree T' that is returned.

First we do a `lookUp` of K in T. This leads us to a node u that either contains K or else u is the successor or predecessor of K in T. Now we can repeatedly rotate at u until u becomes the root of T. At this point, we can split off either the left-subtree or right-subtree of T. This pair of trees is the desired result.

¶20. Complexity. Let us now discuss the worst case complexity of each of the above operations. They are all $\Theta(h)$ where h is the height of the tree. It is therefore desirable to be able to maintain $O(\log n)$ bounds on the height of binary search trees.

> We stress that our rotation-based algorithms for insertion and deletion are slower than the "standard" algorithms which perform only a constant number of pointer re-assignments. Therefore, it seems that rotation-based algorithms may be impractical unless we get other benefits. One possible benefit of rotation will be explored in Chapter 6 on amortization and splay trees.

EXERCISES

Exercise 3.1: Consider the BST of Figure 3(a). Please show all the intermediate trees, not just the final tree.
(a) Perform the deletion of the key 10 this tree using the rotation-based deletion algorithm.
(b) Repeat part (a), using the standard deletion algorithm. ♢

Exercise 3.2: The function VERIFY(u) is supposed return true iff the binary tree rooted at u is a binary search tree with distinct keys:

```
VERIFY(Node u)
    if (u = nil) Return(true)
    if ((u.left ≠ nil) and (u.key < u.left.key)) Return(false)
    if ((u.right ≠ nil) and (u.key > u.right.key)) Return(false)
    Return(VERIFY(u.left)∧VERIFY(u.right))
```

Either argue for it's correctness, or give a counter-example showing it is wrong. ♢

Exercise 3.3: TRUE or FALSE: Recall that a rotation can be implemented with 6 pointer assignments. Suppose a binary search tree maintains successor and predecessor links (denoted u.`succ` and u.`pred` in the text). Now rotation requires 12 pointer assignments. ♢

Exercise 3.4: (a) Implement the above binary search tree algorithms (rotation, lookup, insert, deletion, etc) in your favorite high level language. Assume the binary trees have parent pointers.
(b) Describe the necessary modifications to your algorithms in (a) in case the binary trees do not have parent pointers. ♢

Exercise 3.5: Let T be the binary search tree in figure 3. You should recall the ADT semantics of $T' \leftarrow \texttt{split}(T, K)$ and $\texttt{merge}(T, T')$ in §2. HINT: although we only require that you show the trees at the end of the operations, we recommend that you show selected intermediate stages. This way, we can give you partial credits in case you make mistakes!

(a) Perform the operation $T' \leftarrow \texttt{split}(T, 5)$. Display T and T' after the split.
(b) Now perform $\texttt{insert}(T, 3.5)$ where T is the tree after the operation in (a). Display the tree after insertion.
(c) Finally, perform $\texttt{merge}(T, T')$ where T is the tree after the insert in (b) and T' is the tree after the split in (a). ♢

Exercise 3.6: Give the code for rotation which uses temporary variables. ♢

Exercise 3.7: Instead of minimizing the number of assignments, let us try to minimize the time. To count time, we count each reference to a pointer as taking unit time. For instance, the assignment $u.\texttt{next.prev.prev} \leftarrow u.\texttt{prev}$ costs 5 time units because in addition to the assignment, we have to make access 4 pointers.
(a) What is the rotation time in our 6 assignment solution in the text?
(b) Give a faster rotation algorithm, by using temporary variables. ♢

Exercise 3.8: We could implement a double rotation as two successive rotations, and this would take 12 assignment steps.
(a) Give a simple proof that 10 assignments are necessary.
(b) Show that you could do this with 10 assignment steps. ♢

Exercise 3.9: Open-ended: The problem of implementing $\texttt{rotate}(u)$ without using extra storage or in minimum time (previous Exercise) can be generalized. Let G be a directed graph where each edge ("pointer") has a name (e.g., $\texttt{next}, \texttt{prev}, \texttt{left}, \texttt{right}$) taken from a fixed set. Moreover, there is at most one edge with a given name coming out of each node. Suppose we want to transform G to another graph G', just by reassignment of these pointers. Under what conditions can this transformation be achieved with only one variable u (as in $\texttt{rotate}(u)$)? Under what conditions is the transformation achievable at all (using more intermediate variables? We also want to achieve minimum time. ♢

Exercise 3.10: The goal of this exercise is to show that if T_0 and T_1 are two equivalent binary search trees, then there exists a sequence of rotations that transforms T_0 into T_1. Assume the keys in each tree are distinct. This shows that rotation is a "universal" equivalence transformation. We explore two strategies.
(a) One strategy is to first make sure that the roots of T_0 and T_1 have the same key. Then by induction, we can transform the left- and right-subtrees of T_0 so that they are identical to those of T_1. Let $R_1(n)$ be the worst case number of rotations using this strategy on trees with n keys. Give a tight analysis of $R_1(n)$.
(b) Another strategy is to show that any tree can be reduced to a canonical form. Let us choose the canonical form where our binary search tree is a **left-list** or a **right-list**. A left-list (resp., right-list) is a binary trees in which every node has no right-child (resp., left-child). Let $R_2(n)$ be defined for this strategy in analogy to $R_1(n)$. Give a tight analysis of $R_2(n)$. ♢

Exercise 3.11: Prove Lemma 2, that there is a unique way to order the nodes of a binary tree T that is consistent with any binary search tree based on T. HINT: remember the Fundamental Rule about binary trees. ♢

Exercise 3.12: Implement the Cut(u) operation in a high-level informal programming language. Assume that nodes have parent pointers, and your code should work even if $u.\texttt{parent} = \text{nil}$. Your code should explicitly "delete(v)" after you physically remove a node v. If u has two children, then Cut(u) must be a no-op.

♢

Exercise 3.13: Design an algorithm to find both the successor and predecessor of a given key K in a binary search tree. It should be more efficient than just finding the successor and finding the predecessor independently. ♢

Exercise 3.14: Show that if a binary search tree has height h and u is any node, then a sequence of $k \geq 1$ repeated executions of the assignment $u \leftarrow successor(u)$ takes time $O(h + k)$. ♢

Exercise 3.15: Show how to efficiently maintain the heights of the left and right spines of each node. (Use this in the rotation-based deletion algorithm.) ♢

Exercise 3.16: We refine the successor/predecessor relation. Suppose that T^u is obtained from T by pruning all the proper descendants of u (so u is a leaf in T^u). Then the successor and predecessor of u in T^u are called (respectively) the **external successor** and **predecessor** of u in T Next, if T_u is the subtree at u, then the successor and predecessor of u in T_u are called (respectively) the **internal successor** and **predecessor** of u in T

(a) Explain the concepts of internal and external successors and predecessors in terms of spines.

(b) What is the connection between successors and predecessors to the internal or external versions of these concepts? ♢

Exercise 3.17: Give the rotation-based version of the successor algorithm. ♢

Exercise 3.18: Suppose that we begin with u pointing at the first node of a binary tree, and continue to apply the rotation-based successor (see previous question) until u is at the last node. Bound the number of rotations made as a function of n (the size of the binary tree). ♢

Exercise 3.19: Suppose we allow allow duplicate keys. Under (1), we can modify our algorithms suitably so that all the keys with the same value lie in consecutive nodes of some "right-path chain".

(a) Show how to modify lookup on key K so that we list all the items whose key is K.

(b) Discuss how this property can be preserved during rotation, insertion, deletion.

(c) Discuss the effect of duplicate keys on the complexity of rotation, insertion, deletion. Suggest ways to improve the complexity. ♢

Exercise 3.20: Consider the priority queue ADT. Describe algorithms to implement this ADT when the concrete data structures are binary search trees.

(b) Analyze the complexity of your algorithms in (a). ♢

END EXERCISES

§4. Tree Traversals and Applications

In this section, we describe systematic methods to visit all the nodes of a binary tree. Such methods are called **tree traversals**. Tree traversals provide "algorithmic skeletons" or **shells** for implementing many useful algorithms. We had already seen this concept in ¶2, when implemented ADT operations using linked lists.

Unix fans – shell programming is not what you think it is

¶21. In-order Traversal. There are three systematic ways to visit all the nodes in a binary tree: they are all defined recursively. Perhaps the most important is the **in-order** or **symmetric traversal**. Here is the recursive procedure to perform an in-order traversal of a tree rooted at u:

Fundamental Rule of binary trees!

```
IN-ORDER(u):
Input:  u is root of binary tree T to be traversed.
Output: The in-order listing of the nodes in T.
    0.  BASE(u).
    1.  In-order(u.left).
    2.  VISIT(u).
    3.  In-order(u.right).
```

This recursive program uses two subroutines, or more accurately, macros called BASE and VISIT. For traversals, the BASE macro[5] can be expanded into the following single line of code:

```
BASE(u)≡
    if (u=nil) Return.
```

The VISIT(u) macro is simply:

```
VISIT(u)≡
    Print u.key.
```

To illustrate, consider the two binary trees in figure 2. The numbers on the nodes are keys, but they are not organized into a binary search tree. They simply serve as identifiers.

An in-order traversal of the small tree in Figure 2 will produce $(4, 2, 1, 5, 3)$. For a more substantial example, consider the output of an in-order traversal of the big tree:

$$(7, 4, 12, 15, 8, 2, 9, 5, 10, 1, 3, 13, 11, 14, 6)$$

Basic fact: *if we list the keys of a BST using an inorder traversal, then the keys will be sorted.*

For instance, the in-order traversal of the BST in Figure 3 will simply produce the sequence

$$(1, 2, 3, 4, 5, \ldots, 12, 13, 14, 15).$$

[5] We regard BASE to be a macro call (or an "inline") and not as a subroutine call. This is because the Return statement in BASE is meant to return from the In-Order routine, and not a return from the "BASE subroutine".

This yields an interesting conclusion: *sorting a set S of numbers can be reduced to constructing a binary search tree on a set of nodes with S as their keys.*

¶22. Pre-order Traversal. We can re-write the above In-Order routine succinctly as:

$$IN(u) \equiv [\boxed{\text{BASE}}(u); IN(u.\texttt{left}); \boxed{\text{VISIT}}(u); IN(u.\texttt{right})]$$

Changing the order of Steps 1, 2 and 3 in the In-Order procedure (but always doing Step 1 before Step 3), we obtain two other methods of tree traversal. Thus, if we perform Step 2 before Steps 1 and 3, the result is called the **pre-order traversal** of the tree:

$$PRE(u) \equiv [\boxed{\text{BASE}}(u); \boxed{\text{VISIT}}(u); PRE(u.\texttt{left}); PRE(u.\texttt{right})]$$

Applied to the small tree in figure 2, we obtain $(1, 2, 4, 3, 5)$. The big tree produces

$$(1, 2, 4, 7, 8, 12, 15, 5, 9, 10, 3, 6, 11, 13, 14).$$

¶23. Post-order Traversal. If we perform Step 2 after Steps 1 and 3, the result is called the **post-order traversal** of the tree:

$$POST(u) \equiv [\boxed{\text{BASE}}(u); POST(u.\texttt{left}); POST(u.\texttt{right}); \boxed{\text{VISIT}}(u)]$$

Using the trees of Figure 2, we obtain the output sequences $(4, 2, 5, 3, 1)$ and

$$(7, 15, 12, 8, 4, 9, 10, 5, 2, 13, 14, 11, 6, 3, 1).$$

¶24. Applications of Tree Traversal: Shell Programming Tree traversals may not appear interesting on their own right. However, they serve as shells for solving many interesting problems. That is, many algorithms can be programmed by taking a tree traversal shell, and replacing the named macros by appropriate code: for tree traversals, we have two such macros, called BASE and VISIT.

To illustrate shell programming, suppose we want to compute the height of each node of a BST. Assume that each node u has a variable $u.H$ that is to store the height of node u. If we have recursive computed the values of $u.\texttt{left}.H$ and $u.\texttt{right}.H$, then we see that the height of u can be computed as

$$u.H = 1 + \max\{u.\texttt{left}.H + u.\texttt{right}.H\}.$$

This suggests the use of post-order shell to solve the height problem: We keep the previous BASE subroutine, but modify $VISIT(u)$ to the following task: computing height in post-order

```
VISIT(u)
    if (u.left = nil) then L ← −1.
        else L ← u.left.H.
    if (u.right = nil) then R ← −1.
        else R ← u.right.H.
    u.H ← 1 + max{L, R}.
```

On the other hand, suppose we want to compute the depth of each node. Again, assume each node u stores a variable $u.D$ to record its depth. Then, assuming that $u.D$ has been computed, then we could computing depth in pre-order

easily compute the depths of the children of u using

$$u.\texttt{left}.D = u.\texttt{right}.D = 1 + u.D.$$

This suggests that we use the pre-order shell for computing depth.

¶25. Return Shells. For some applications, we want a version of the above traversal routines that return some value. We call them "return shells" here. Let us illustrate this by modifying the postorder shell POST(u) into a new version rPOST(u) which returns a value of type T. For instance, T might be the type integer or the type node. The returned value from recursive calls are then passed to the VISIT macro:

```
rPOST(u)
    rBASE(u).
    L ← rPOST(u.left).
    R ← rPOST(u.right).
    rVISIT(u, L, R).
```

Note that both $rBASE(u)$ and $rVISIT(u, L, R)$ returns some value of type T.

As an application of this rPOST routine, consider our previous solution for computing the height of binary trees. There we assume that every node u has an extra field called $u.H$ that we used to store the height of u. Suppose we do not want to introduce this extra field for every node. Instead of POST(u), we can use rPOST(u) to return the height of u. How can we do this? First, BASE(u) should be modified to return the height of nil nodes:

```
rBASE(u)≡
    if (u=nil) Return(−1).
```

Second, we must re-visit the VISIT routine, modifying (simplifying!) it as follows: no pun intended

```
rVISIT(u, L, R)
    Return(1 + max{L, R}).
```

The reader can readily check that rPOST solves the height problem elegantly. As another application of such "return shell", suppose we want to check if a binary tree is a binary search tree. This is explored in Exercises below.

The motif of using shell programs such as BASE and VISIT will be further elaborated when we study graph traversals. Indeed, we can view graph traversals as a generalization of tree traversal. Using shells is a great unifying aspect in the study of traversal algorithms: we cannot over emphasize this point. Pay attention when the professor says this

EXERCISES

Exercise 4.1: Give the in-order, pre-order and post-order listing of the tree in Figure 14. ♢

Exercise 4.2: Tree traversals.

(a) Let the in-order and pre-order traversal of a binary tree T with 10 nodes be $(a, b, c, d, e, f, g, h, i, j)$ and $(f, d, b, a, c, e, h, g, j, i)$, respectively. Draw the tree T.

(b) Prove that if we have the pre-order and in-order listing of the nodes in a binary tree, we can reconstruct the tree.

(c) Consider the other two possibilities: (c.1) pre-order and post-order, and (c.2) in-order and post-order. State in each case whether or not they have the same reconstruction property as in (b). If so, prove it. If not, show a counter example.

(d) Redo part(c) for full binary trees. Recall that in a full binary tree, each node either has no children or 2 children. ♢

Exercise 4.3:

(a) Here is the set of keys from post-order traversal of a binary search tree:

$$2, 1, 4, 3, 6, 7, 9, 11, 10, 8, 5, 13, 16, 15, 14, 12$$

Draw this binary search tree.

(b) Describe the general algorithm to reconstruct a BST from its post-order traversal. ♢

Exercise 4.4: Use shell programming to give an algorithm SIZE(u) that returns the number of nodes in the subtree rooted at u. Do not assume any additional fields in the nodes. ♢

Exercise 4.5: Let $size(u)$ be the number of nodes in the tree rooted at u. Say that node u is **size-balanced** if

$$1/2 \leq size(u.\texttt{left})/size(u.\texttt{right}) \leq 2$$

where a leaf node is size-balanced by definition.

(a) Use shell programming to compute the routine $B(u)$ which returns $size(u)$ if each node in the subtree at u is balanced, and $B(u) = -1$ otherwise. Do not assume any additional fields in the nodes or that the size information is available.

(b) Suppose you know that $u.\texttt{left}$ and $u.\texttt{right}$ are size-balanced. Give a routine called $REBALANCE(u)$ that uses rotations to make u balanced. Assume each node v has an extra field $u.SIZE$ whose value is $size(u)$ (you must update this field as you rotate).

♢

Exercise 4.6: Show how to use the pre-order shell to compute the depth of each node in a binary tree. Assume that each node u has a depth field, $u.D$. ♢

Exercise 4.7: Give a recursive routine called $CheckBST(u)$ which checks whether the binary tree T_u rooted at a node u is a binary search tree (BST). You must figure out the information to be returned by $CheckBST(u)$; this information should also tell you whether T_u is BST or not. Assume that each non-nil node u has the three fields, $u.\texttt{key}, u.\texttt{left}, u.\texttt{right}$. ♢

Exercise 4.8: A student proposed a different approach to the previous question. Let $minBST(u)$ and $maxBST(u)$ compute the minimum and maximum keys in T_u, respectively. These subroutines are easily computed in the obvious way. For simplicity, assume all keys are distinct and $u \neq \mathsf{nil}$ in these arguments. The recursive subroutine is given as follows:

```
CheckBST(u)
▷ Returns largest key in T_u if T_u is BST
▷ Returns +∞ if not BST
▷ Assume u is not nil
    If (u.left ≠ nil)
        L ← maxBST(u.left)
        If (L > u.key or L = ∞) return(∞)
    If (u.right ≠ nil)
        R ← minBST(u.right)
        If (R < u.key or R = ∞) return(∞)
    Return (CheckBST(u.left) ∧ (CheckBST(u.right)
```

Is this program correct? Bound its complexity. HINT: Let the "root path length" of a node be the length of its path to the root. The "root path length" of a binary tree T_u is the sum of the root path lengths of all its nodes. The complexity is related to this number. ♢

Exercise 4.9: Like the previous problem, we want to check if a binary tree is a BST. Write a recursive algorithm called $SlowBST(u)$ which solves the problem, except that the running time of your solution must be provably exponential-time. If you like, your solution may consist of mutually recursive algorithms. Your overall algorithm must achieve this exponential complexity without any trivial redundancies. E.g., we should not be able to delete statements from your code and still achieve a correct program. Thus, we want to avoid a trivial solutions of this kind:

```
SlowBST(u)
    Compute the number n of nodes in T_u
    Do for 2^n times:
        FastBST(u)
```

♢

END EXERCISES

§5. Variations on Binary Trees

This is an optional section, for those who wants a deeper understanding of binary trees and their applications. We will discuss extended binary trees, alternative ways to use binary trees in search structures, and the notion of implicit binary search trees.

¶26. Extended binary trees. There is an alternative view of binary trees; following Knuth [4, p. 399], we call them **extended binary trees**. For emphasis, the original version will be called **standard binary trees**. In the extended trees, every node has 0 or 2 children; nodes with no children are called[6] **nil nodes** while the other nodes are called **non-nil nodes**. See figure 10(a) for a standard binary tree and figure 10(b) for the corresponding extended version. In this figure, we see a common convention (following Knuth) of representing nil nodes by black squares.

The bijection between extended and standard binary trees is given as follows:

[6] A binary tree in which every node has 2 or 0 children is said to be "full". Knuth calls the nil nodes "external nodes". A path that ends in an external node is called an "external path".

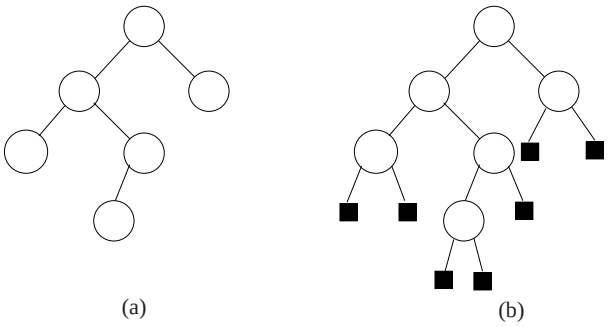


Figure 10: Binary Trees: (a) standard, (b) extended.

1. For any extended binary tree, if we delete all its nil nodes, we obtain a standard binary tree.
2. Conversely, for any standard binary tree, if we give every leaf two nil nodes as children and for every internal node with one child, we give it one nil node as child, then we obtain a corresponding extended binary tree.

Who cares about nil nodes?

In view of this correspondence, we could switch between the two viewpoints depending on which is more convenient. Generally, we avoid drawing the nil nodes since they just double the number of nodes without conveying new information. In fact, nil nodes cannot store data or items. One reason we explicitly introduce them is that it simplifies the description of some algorithms (e.g., red-black tree algorithms). The "nil node" terminology may be better appreciated when we realize that in conventional realization of binary trees, we allocate two pointers to every node, regardless of whether the node has two children or not. The lack of a child is indicated by making the corresponding pointer take the nil value. We extend the notion of extended binary tree to **extended binary search tree**. Here, the non-nil nodes store keys in the usual nodes but the nil nodes do not hold keys (obviously).

The concept of a "leaf" of an extended binary tree is apt to cause some confusion: we shall use the "leaf" terminology so as to be consistent with standard binary trees. A node of an extended binary tree is called a **leaf** if it is the leaf of the corresponding standard binary tree. Alternatively, a leaf in an extended binary tree is a node with two nil nodes as children. *Thus a nil node is never a leaf.*

¶27. Exogenous versus Endogenous Search Structures Recall that each key is associated with some data, and such key-data pairs constitute the items for searching. There are two ways to organize such items. One way is to directly store the data with the key. The other way is for the key to be paired with a pointer to the data. Following[7] Tarjan [9], we call the latter organization an **exogenous search structure** In contrast, if the data is directly stored with the key, it is an **endogenous search structure**. What is the relative advantage of either form? The exogenous case has an extra level of indirection (the pointer) which uses extra space. But on the other hand, it means that the actual data can be freely re-organized more easily and independently of the search structure. In databases, this freedom is important, and the exogenous search structure are called "indexes". Database users can freely create and destroy such indexes for the set of items. This allows a collection of items can be searched using different search criteria. The concept of (a, b)-trees below illustrates such exogenous search structures.

¶28. Duplicate keys. We normally assume that the keys in a BST are distinct unless otherwise noted. But let us now briefly consider BST whose keys are not necessarily unique or distinct. One way to

[7] He used this classification for linked lists data structure.

handle duplicate keys is to require the following **right-path rule**: *all items with the same key must lie on consecutive nodes of some right-path.* We can view all the equal-key nodes on this right-path as a super-node for the purposes of maintaining height-balanced trees such as AVL trees. Before discussing how to maintain this right-path rule, let us discuss how `lookUp` must be modified. When we look up on a key k, we can just return the first node that contains the key k. Alternatively, if there is a secondary key besides the (primary) key which might distinguish among the different items with primary key k, we can search the right-path for this secondary key. Now we must modify all our algorithms to preserve the right-path rule. In particular, insertion and rotation should be appropriately modified. What about deletion? If the argument of deletion is the node to be deleted, it is clearly easy to maintain this property. If the argument of deletion is a key k, we can either delete all items whose key is k or rely on secondary keys to distinguish among the items with key k.

Instead of the right-path rule, we could put all the equal-key items in an auxiliary linked list attached to a node. There are pros and cons in either approach. The "right path" organization of duplicate keys do not need any auxiliary structures. If the expected number of duplicated keys is small, it may be the best solution.

¶29. Auxiliary Information. In many applications, additional information must be maintained at each node of the binary search tree. We already mentioned the predecessor and successor links. Another information is the the size of the subtree at a node. Some of this information is independent, while other is dependent or **derived**. Maintaining the derived information under the various operations is usually straightforward. In all our examples, the derived information is **local** in the following sense that *the derived information at a node u can only depend on the information stored in the subtree at u.* We will say that derived information is **strongly local** if it depends only on the independent information at node u, together with all the information at its children (whether derived or independent).

¶30. Parametric Binary Search Trees. Perhaps the most interesting variation of binary search trees is when the keys used for comparisons are only implicit. The information stored at nodes allows us to make a "comparison" and decide to go left or to go right at a node but this comparison may depend on some external data beyond any explicitly stored information. We illustrate this concept in the lecture on convex hulls in Lecture V.

¶31. Implicit Binary Trees. By an implicit tree, we mean one that does not have explicit pointers which determine the parent/child relationships of nodes. An example is the **heap structure**: this is defined to be binary tree whose nodes are indexed by integers following this rule: the root is indexed 1, and if a node has index i, then its left and right children are indexed by $2i$ and $2i+1$, respectively. Moreover, if the binary tree has n nodes, then the set of its indices is the set $\{1, 2, \ldots, n\}$. A heap structure can therefore be represented naturally by an array $A[1..n]$, where $A[i]$ represents the node of index i. If, at the ith node of the heap structure, we store a key $A[i]$ and these keys satisfy the **heap order property** for each $i = 1, \ldots, n$,

$$HO(i): \quad A[i] \leq \min\{A[2i], A[2i+1]\}. \tag{4}$$

In (4), it is understood that if $2i > n$ (resp., $2i+1 > n$) then $A[2i]$ ($A[2i+1]$) is taken to be ∞. Then we call the binary tree a **heap**. Here is an array that represents a heap:

$$A[1..9] = [1, 4, 2, 5, 6, 3, 8, 7, 9].$$

In the exercises we consider algorithms for insertion and deletion from a heap. This leads to a highly efficient method for sorting elements in an array, in place.

In general, implicit data structures are represented by an array with some rules for computing the parent/child relations. By avoiding explicit pointers, such structures can be very efficient to navigate.

EXERCISES

Exercise 5.1: Describe what changes is needed in our binary search tree algorithms for the exogenous case. ♢

Exercise 5.2: Suppose we insist that for exogenous binary search trees, each of the keys in the internal nodes really correspond to keys in stored items. Describe the necessary changes to the deletion algorithm that will ensure this property. ♢

Exercise 5.3: Consider the usual binary search trees in which we no longer assume that keys in the items are unique. State suitable conventions for what the various operations mean in this setting. E.g., `lookUp`(K) means find any item whose key is K or find all items whose keys are equal to K. Describe the corresponding algorithms. ♢

Exercise 5.4: Describe the various algorithms on binary search trees that store the size of subtree at each node. ♢

Exercise 5.5: Recall the concept of heaps in the text. Let $A[1..n]$ be an array of real numbers. We call A an **almost-heap at** i there exists a number such that if $A[i]$ is replaced by this number, then A becomes a heap. Of course, a heap is automatically an almost-heat at any i.
(i) Suppose A is an almost-heap at i. Show how to convert A into a heap be pairwise-exchange of array elements. Your algorithm should take no more than $\lg n$ exchanges. Call this the $Heapify(A, i)$ subroutine.
(ii) Suppose $A[1..n]$ is a heap. Show how to delete the minimum element of the heap, so that the remaining keys in $A[1..n-1]$ form a heap of size $n-1$. Again, you must make no more than $\lg n$ exchanges. Call this the $DeleteMin(A)$ subroutine.
(iii) Show how you can use the above subroutines to sort an array in-place in $O(n \log n)$ time.
♢

Exercise 5.6: Normally, each node u in a binary search tree maintains two fields, a key value and perhaps some balance information, denoted u.KEY and u.BALANCE, respectively. Suppose we now wish to "augment" our tree T by maintaining two additional fields called u.PRIORITY and u.MAX. Here, u.PRIORITY is an integer which the user arbitrarily associates with this node, but u.MAX is a pointer to a node v in the subtree at u such that v.PRIORITY is maximum among all the priorities in the subtree at u. (Note: it is possible that $u = v$.) Show that rotation in such augmented trees can still be performed in constant time.

♢

END EXERCISES

§6. AVL Trees

AVL trees is the first known family of balanced trees. By definition, an AVL tree is a binary search tree in which the left subtree and right subtree at each node differ by at most 1 in height. They also have relatively simple insertion/deletion algorithms.

More generally, define the **balance** of any node u of a binary tree to be the height of the left subtree minus the height of the right subtree:

$$balance(u) = ht(u.\texttt{left}) - ht(u.\texttt{right}).$$

The node is **perfectly balanced** if the balance is 0. It is **AVL-balanced** if the balance is either 0 or ± 1. Our insertion and deletion algorithms will need to know this balance information at each node. Thus we need to store at each AVL node a 3-valued variable. Theoretically, this space requirement amounts to $\lg 3 < 1.585$ bits per node. Of course, in practice, AVL trees will reserve 2 bits per node for the balance information (but see Exercise).

Let us first prove that the family of AVL trees is a balanced family. It is best to introduce the function $\mu(h)$, defined as the minimum number of nodes in any AVL tree with height h. The first few values are

$$\mu(-1) = 0, \qquad \mu(0) = 1, \qquad \mu(1) = 2, \qquad \mu(2) = 4.$$

It seems clear that $\mu(0) = 1$ since there is a unique tree with height 0. The other values are not entirely obvious. To see[8] that $\mu(1) = 2$, *we must define the height of the empty tree to be* -1. This explains why $\mu(-1) = 0$. We can verify $\mu(2) = 4$ by case analysis.

Consider an AVL tree T_h of height h and of size $\mu(h)$ (i.e., it has $\mu(h)$ nodes). Clearly, among all AVL trees of height h, T_h has the minimum size. For this reason, we call call T_h a **min-size AVL tree** (for height h). Figure 11 shows the first few min-size AVL trees. Of course, we can exchange the roles of any pair of siblings of such a tree to get another min-size AVL tree. Using this, we could compute the number of non-isomorphic min-sized AVL trees of a given height. But we can define the **canonical min-size AVL trees** to be the ones in which the balance of each non-leaf node is $+1$. Note that we draw such canonical trees in figure 11.

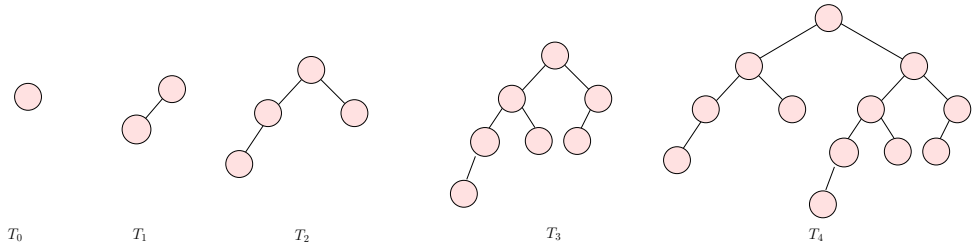


Figure 11: Canonical min-size AVL trees of heights 0, 1, 2, 3 and 4.

In general, $\mu(h)$ is seen to satisfy the recurrence

$$\mu(h) = 1 + \mu(h-1) + \mu(h-2), \qquad (h \geq 1). \tag{5}$$

This equation says that the min-size tree of height h having two subtrees which are min-size trees of heights $h-1$ and $h-2$, respectively. For instance, $\mu(2) = 1 + \mu(1) + \mu(0) = 1 + 2 + 1 = 4$, as we found by case analysis above. We similarly check that the recurrence (5) holds for $h = 1$.

From (5), we have $\mu(h) \geq 2\mu(h-2)$ for $h \geq 1$. It is then easy to see by induction that $\mu(h) \geq 2^{h/2}$ for all $h \geq 1$. Writing $C = \sqrt{2} = 1.4142\ldots$, we have thus shown

$$\mu(h) \geq C^h, \qquad (h \geq 1).$$

[8] For instance, if we say the height of the empty tree is $-\infty$, then $\mu(1) = 3$. This definition of AVL trees could certainly be supported. See Exercise for an exploration of this idea.

The next lemma improves this simple lower bound on $\mu(h)$ and also provide a matching upper bound: let $\phi = \frac{1+\sqrt{5}}{2} > 1.6180$. This is the golden ratio and it is easily seen to be the positive root of the quadratic equation $x^2 - x - 1 = 0$. Hence, $\phi^2 = \phi + 1$ (in words: to square ϕ, you add 1).

LEMMA 4. *For $h \geq 0$, we have*

$$\phi^h \leq \mu(h) < 2\phi^h. \tag{6}$$

Proof. First we prove $\mu(h) \geq \phi^h$: $\mu(0) = 1 \geq \phi^0$ and $\mu(1) = 2 \geq \phi^1$. For $h \geq 2$, we have

$$\mu(h) > \mu(h-1) + \mu(h-2) \geq \phi^{h-1} + \phi^{h-2} = (\phi + 1)\phi^{h-2} = \phi^h.$$

Next, to prove $\mu(h) < 2\phi^h$, we will strengthen our hypothesis to $\mu(h) \leq 2\phi^h - 1$. Clearly, $\mu(0) = 1 \leq 2\phi^0 - 1$ and $\mu(1) = 2 \leq 2\phi^1 - 1$. Then for $h \geq 2$, we have

$$\mu(h) = 1 + \mu(h-1) + \mu(h-2) \leq 1 + (\phi^{h-1} - 1) + (\phi^{h-2} - 1) = (\phi + 1)\phi^{h-2} - 1 = \phi^h - 1.$$

Q.E.D.

The bounds of this lemma are asymptotically tight; but an exercise below will further sharpen the estimate. Actually, it is the lower bound that is more important: this lower bound says that min-size AVL

Let us derive a consequence of the lower bound on $\mu(h)$. If an AVL tree has n nodes and height h then

$$\mu(h) \leq n$$

by definition of $\mu(h)$. The lower bound in (6) then implies $\phi^h \leq n$. Taking logs, we obtain

$$h \leq \log_\phi(n) = (\log_\phi 2) \lg n < 1.4404 \lg n.$$

This constant of 1.44 is clearly tight in view of lemma 4. Thus the height of AVL trees are at most 44% more than the absolute minimum. We have proved:

COROLLARY 5. *The family of AVL trees is balanced.*

¶32. Insertion and Deletion Algorithms. These algorithms for AVL trees are relatively simple, as far as balanced trees go. In either case there are two phases:

UPDATE PHASE: Insert or delete as we would in a binary search tree. REMARK: We assume here the *standard* deletion algorithm, not its rotational variant. Furthermore, the node containing the deleted key and the node we *physically* removed may be different.

REBALANCE PHASE: Let x be the parent of node that was just inserted, or just *physically* deleted, in the UPDATE PHASE. We now retrace the path from x towards the root, rebalancing nodes along this path as necessary. For reference, call this the **rebalance path**.

It remains to give details for the REBALANCE PHASE. If every node along the rebalance path is balanced, then there is nothing to do in the REBALANCE PHASE. Otherwise, let u be the first unbalanced node we encounter as we move upwards from x to the root. It is clear that u has a balance of ± 2. In general, we fix the balance at the "current" unbalanced node and continue searching upwards along the rebalance path for the next unbalanced node. Let u be the current unbalanced node. By symmetry, we may suppose that u has balance 2. Suppose its left child is node v and has height $h + 1$. Then its right child v' has height $h - 1$. This situation is illustrated in Figure 12.

By definition, all the proper descendants of u are balanced. The current height of u is $h + 2$. In any case, let the current heights of the children of v be h_L and h_R, respectively.

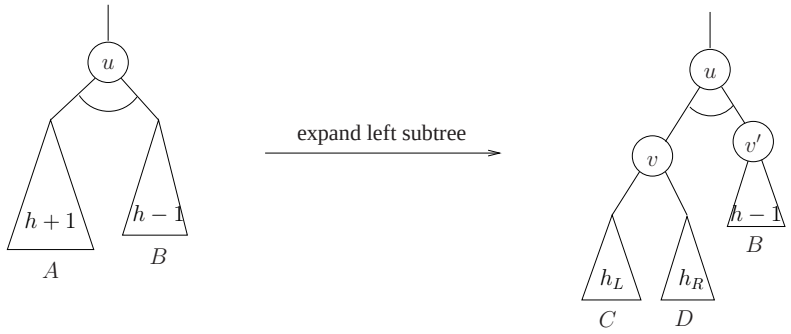


Figure 12: Node u is unbalanced after insertion or deletion.

¶33. Insertion Rebalancing. Suppose that this imbalance came about because of an insertion. What was the heights of u, v and v' before the insertion? It is easy to see that the previous heights are (respectively)

$$h + 1, h, h - 1.$$

The inserted node x must be in the subtree rooted at v. Clearly, the heights h_L, h_R of the children of v satisfy $\max(h_L, h_R) = h$. Since v is currently balanced, we know that $\min(h_L, h_R) = h$ or $h - 1$. But in fact, we claim that $\min(h_L, h_R) = h - 1$. To see this, note that if $\min(h_L, h_R) = h$ then the height of v *before* the insertion was also $h + 1$ and this contradicts the initial AVL property at u. Therefore, we have to address the following two cases.

CASE (I.1): $h_L = h$ and $h_R = h - 1$. This means that the inserted node is in the left subtree of v. In this case, if we rotate v, the result would be balanced. Moreover, the height of u is $h + 1$.

CASE (I.2): $h_L = h - 1$ and $h_R = h$. This means the inserted node is in the right subtree of v. In this case let us expand the subtree D and let w be its root. The two children of w will have heights of $h - 1$ and $h - 1 - \delta$ ($\delta = 0, 1$). It turns out that it does not matter which of these is the left child (despite the apparent asymmetry of the situation). If we double rotate w (*i.e.*, $\texttt{rotate}(w), \texttt{rotate}(w)$), the result is a balanced tree rooted at w of height $h + 1$.

In both cases (I.1) and (I.2), the resulting subtree has height $h + 1$. Since this was height before the insertion, there are no unbalanced nodes further up the path to the root. Thus the insertion algorithm terminates with at most two rotations.

For example, suppose we begin with the AVL tree in Figure 14, and we insert the key 9.5. The resulting transformations is shown in Figure 15.

¶34. Deletion Rebalancing. Suppose the imbalance in Figure 12 comes from a deletion. The previous heights of u, v, v' must have been

$$h + 2, h + 1, h$$

and the deleted node x must be in the subtree rooted at v'. We now have three cases to consider:

CASE (D.1): $h_L = h$ and $h_R = h - 1$. This is like case (I.1) and treated in the same way, namely by performing a single rotation at v. Now u is replaced by v after this rotation, and the new height of v is $h + 1$. Now u is AVL balanced. However, since the original height is $h + 2$, there may be unbalanced node further up the root path. Thus, this is a non-terminal case (i.e., we have to continue checking for balance further up the root path).

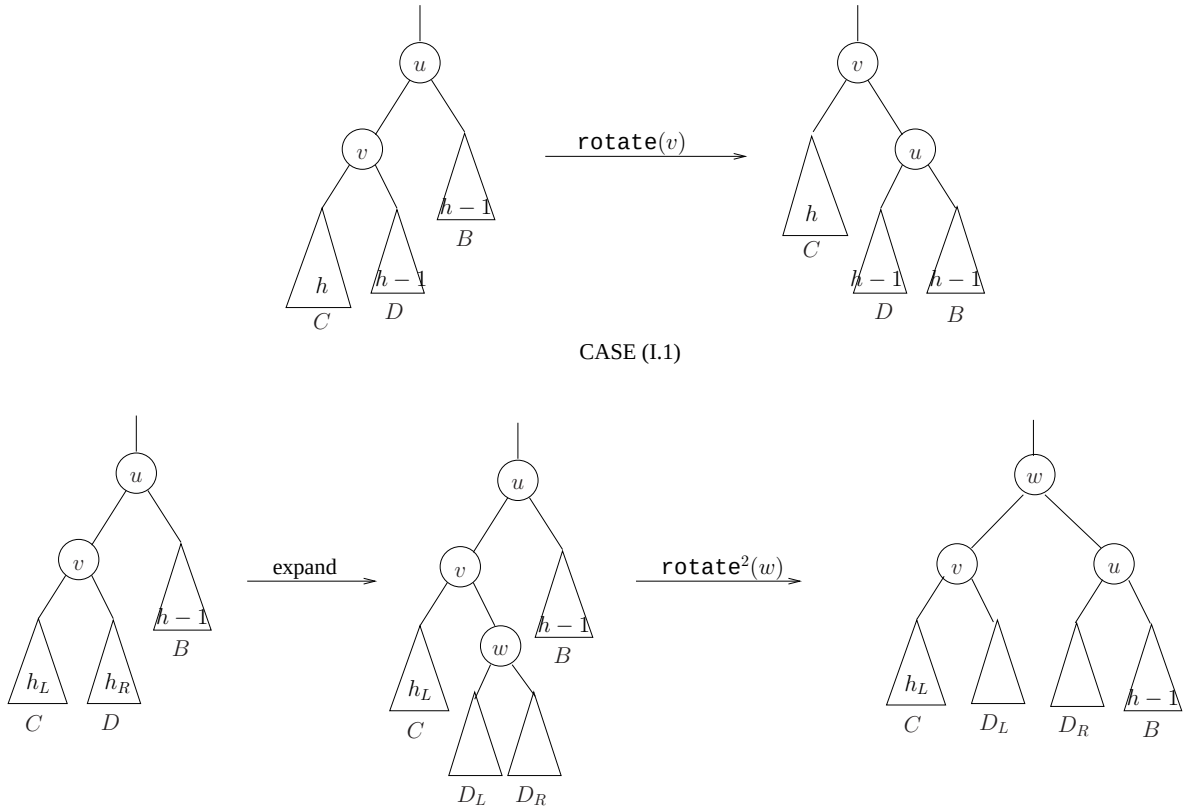


Figure 13: CASE (I.1): `rotate`(v), CASE (I.2): `rotate`$^2(w)$.

CASE (D.2): $h_L = h - 1$ and $h_R = h$. This is like case (I.2) and treated the same way, by performing a double rotation at w. Again, this is a non-terminal case.

CASE (D.3): $h_L = h_R = h$. This case is new, and is illustrated in Figure 16. We simply rotate at v. We check that v is balanced and has height $h + 2$. Since v is in the place of u which has height $h + 2$ originally, we can safely terminate the rebalancing process.

This completes the description the insertion and deletion algorithms for AVL trees. In illustration, suppose we delete key 13 from Figure 14. After deleting 13, the node 14 is unbalanced. This is restored by a single rotation at 15. Now, the root containing 12 is unbalanced. Another single rotation at 5 will restore balance. The result is shown in Figure 17.

Both insertion and deletion take $O(\log n)$ time. In case of deletion, we may have to do $O(\log n)$ rotations but a single or double rotation suffices for insertion.

¶35. Maintaining Balance Information. In order to carry out the rebalancing algorithm, we need to check the balance condition at each node u. If node u stores the height of u in some field, $u.H$ then we can do this check. If the AVL tree has n nodes, $u.H$ may need $\Theta(\lg \lg n)$ bits to represent the height. However, it is possible to get away with just 2 bits: we just need to indicate three possible states $(00, 01, 10)$ for each node u. Let 00 mean that $u.$`left` and $u.$`right` have the same height, and 01

Hey, I thought it is $\Theta(\lg n)$!

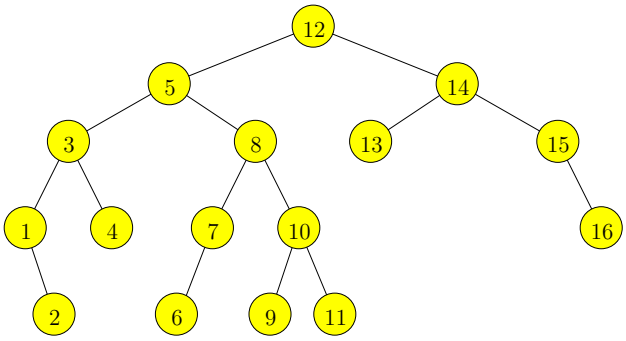


Figure 14: An AVL tree

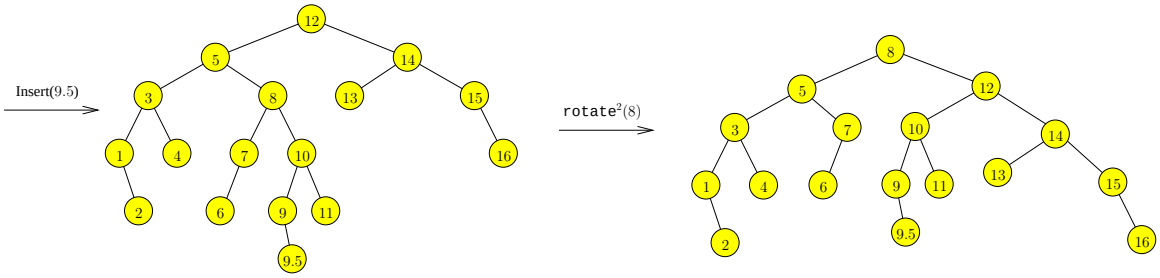


Figure 15: Inserting 9.5 into an AVL tree

mean that $u.\texttt{left}$ has height one less than $u.\texttt{right}$, and similarly for 10. In simple implementations, we could just use an integer to represent this information. We leave it as an exercise to determine how to use these bits during rebalancing.

¶36. Relaxed Balancing. Larsen [5] shows that we can decouple the rebalancing of AVL trees from the updating of the maintained set. In the semi-dynamic case, the number of rebalancing operations is constant in an amortized sense (amortization is treated in Chapter 5).

EXERCISES

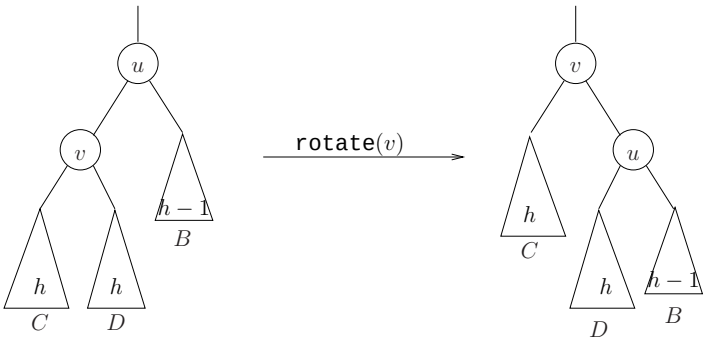


Figure 16: CASE (D.3): $\texttt{rotate}(v)$

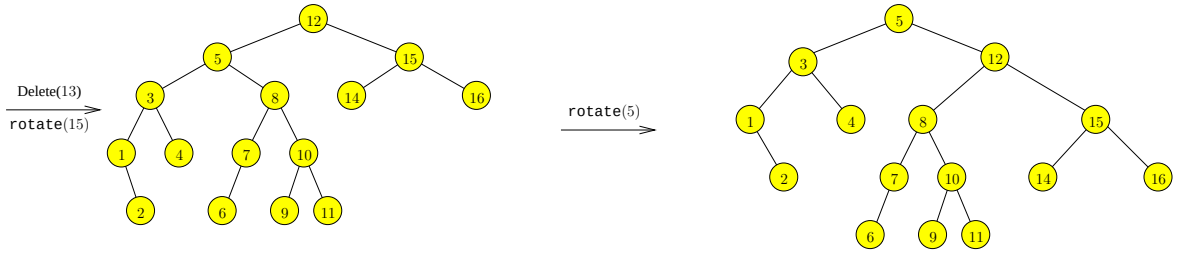


Figure 17: Deleting 13 from the AVL tree in Figure 14

Exercise 6.1: Let T be the AVL tree in Figure 3(a). As usual, show intermediate trees, not just the final one.
(a) Delete the key 10 from T.
(b) Insert the key 2.5 into T. This question is independent of part (a).

Re-do parts (a) and (b), but using the AVL tree in Figure 3(b) instead. ♢

Exercise 6.2: Give an algorithm to check if a binary search tree T is really an AVL tree. Your algorithm should take time $O(|T|)$. HINT: Use shell programming.

♢

Exercise 6.3: What is the minimum number of nodes in an AVL tree of height 10? ♢

Exercise 6.4: My pocket calculator tells me that $\log_\phi 100 = 9.5699\cdots$. What does this tell you about the height of an AVL tree with 100 nodes? ♢

Exercise 6.5: Draw an AVL T with minimum number of nodes such that the following is true: there is a node x in T such that if you delete this node, the AVL rebalancing will require two rebalancing acts. Note that a double-rotation counts as one, not two, rebalancing act. Draw T and the node x. ♢

Exercise 6.6: Consider the AVL tree in Figure 18.

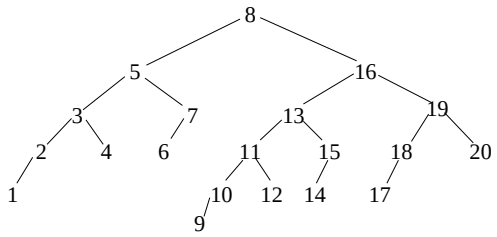


Figure 18: An AVL Tree for deletion

(a) Find all the keys that we can delete so that the rebalancing phase requires two rebalancing acts.
(b) Among the keys in part (a), which deletion has a double rotation among its rebalancing acts?
(c) Please delete one such key, and draw the AVL tree after each of the rebalancing acts. ♢

Exercise 6.7: Consider the height range for AVL trees with n nodes.
(a) What is the range for $n = 15$? $n = 20$ nodes?
(b) Is it true that there are arbitrarily large n such that AVL trees with n nodes has a unique height? ♢

Exercise 6.8: Draw the AVL trees after you insert each of the following keys into an initially empty tree: $1, 2, 3, 4, 5, 6, 7, 8, 9$ and then $19, 18, 17, 16, 15, 14, 13, 12, 11$. ♢

Exercise 6.9: Insert into an initially empty AVL tree the following sequence of keys: $1, 2, 3, \ldots, 14, 15$.
(a) Draw the trees at the end of each insertion as well as after each rotation or double-rotation. [View double-rotation as an indivisible operation].
(b) Prove the following: if we continue in this manner, we will have a complete binary tree at the end of inserting key $2^n - 1$ for all $n \geq 1$. ♢

Exercise 6.10: Starting with an empty tree, insert the following keys in the given order: $13, 18, 19, 12, 17, 14, 15, 16$. Now delete 18. Show the tree after each insertion and deletion. If there are rotations, show the tree just after the rotation. ♢

Exercise 6.11: Draw two AVL trees, with n keys each: the two trees must have different heights. Make n as small as you can. ♢

Exercise 6.12: TRUE or FALSE: In CASE (D.3) of AVL deletion, we performed a single rotation at node v. This is analogous to CASE (D.1). Could we have also have performed a double rotation at w, in analogy to CASE (D.2)? ♢

Exercise 6.13: Let $M(h)$ be the number of non-isomorphic min-size AVL trees of height h. Give a recurrence for $M(h)$. How many non-isomorphic min-size AVL trees are there of heights 3 and 4? Provide sharp upper and lower bounds on $M(h)$. ♢

Exercise 6.14: Improve the lower bound $\mu(h) \geq \phi^h$ by taking into consideration the effects of "$+1$" in the recurrence $\mu(h) = 1 + \mu(h-1) + \mu(h-2)$.
(a) Show that $\mu(h) \geq F(h-1) + \phi^h$ where $F(h)$ is the h-th Fibonacci number. Recall that $F(h) = h$ for $h = 0, 1$ and $F(h) = F(h-1) + F(h-2)$ for $h \geq 2$.
(b) Further improve (a). ♢

Exercise 6.15: Prove the following connection between ϕ (golden ratio) and F_n (the Fibonacci numbers):

$$\phi^n = \phi F_n + F_{n-1}, \qquad (n \geq 1)$$

Note that we ignore the case $n = 0$. ♢

Exercise 6.16: Recall that at each node u of the AVL tree, we can represent its balance state using a 2-bit field called $u.BAL$ where $u.BAL \in \{00, 01, 10\}$.
(a) Show how to maintain these fields during an insertion.
(b) Show how to maintain these fields during a deletion. ♢

Exercise 6.17: Allocating one bit per AVL node is sufficient if we exploit the fact that leaf nodes are always balanced allow their bits to be used by the internal nodes. Work out the details for how to do this. ♢

Exercise 6.18: It is even possible to allocate no bits to the nodes of a binary search tree. The idea is to exploit the fact that in implementations of AVL trees, the space allocated to each node is constant. In particular, the leaves have two null pointers which are basically unused space. We can use this space to store balance information for the internal nodes. Figure out an AVL-like balance scheme that uses no extra storage bits. ♢

Exercise 6.19: Relaxed AVL Trees

Let us define **AVL(2) balance condition** to mean that at each node u in the binary tree, $|balance(u)| \leq 2$.

(a) Derive an upper bound on the height of a AVL(2) tree on n nodes.

(b) Give an insertion algorithm that preserves AVL(2) trees. Try to follow the original AVL insertion as much as possible; but point out differences from the original insertion.

(c) Give the deletion algorithm for AVL(2) trees. ♢

Exercise 6.20: To implement we reserve 2 bits of storage per node to represent the balance information. This is a slight waste because we only use 3 of the four possible values that the 2 bits can represent. Consider the family of "biased-AVL trees" in which the balance of each node is one of the values $b = -1, 0, 1, 2$.

(a) In analogy to AVL trees, define $\mu(h)$ for biased-AVL trees. Give the general recurrence formula and conclude that such trees form a balanced family.

(b) Is it possible to give an $O(\log n)$ time insertion algorithm for biased-AVL trees? What can be achieved? ♢

Exercise 6.21: We introduce a new notion of 'height' of an AVL tree: If node u is null, $h'(u) = -2$ (this is new!), and if u has no children, $h'(u) = 0$ (as usual). Recursively, $h'(u) = 1 + \max\{h'(u_L), h'(u_R)\}$ as before. Let 'AVL' (AVL in quotes) trees refer be those trees that are AVL-balanced using h' as our new notion of height. We compare the original AVL trees with 'AVL' trees.

(a) TRUE or FALSE: every 'AVL' tree is an AVL tree.

(b) Let $\mu'(h)$ be defined (similar to $\mu(h)$ in the text) as the minimum number of nodes in an 'AVL' tree of height h. Determine $\mu'(h)$ for all $h \leq 5$.

(c) Prove the relationship $\mu'(h) = \mu(h) + F(h)$ where $F(h)$ is the standard Fibonacci numbers.

(d) Give a good upper bound on $\mu'(h)$.

(e) What is one conceptual difficulty of trying to use the family of 'AVL' trees as a general search structure? ♢

Exercise 6.22: A node in a binary tree is said to be **full** if it has exactly two children. A **full binary tree** is one where all internal nodes are full.

(a) Prove full binary tree have an odd number of nodes.

(b) Show that 'AVL' trees as defined in the previous question are full binary trees. ♢

Exercise 6.23: The AVL insertion algorithm makes two passes over its search path: the first pass is from the root down to a leaf, the second pass goes in the reverse direction. Consider the following idea for a "one-pass algorithm" for AVL insertion: during the first pass, before we visit a node

u, we would like to ensure that (1) its height is less than or equal to the height of its sibling. Moreover, (2) if the height of u is equal to the height of its sibling, then we want to make sure that if the height of u is increased by 1, the tree remains AVL.

The following example illustrates the difficulty of designing such an algorithm:

Imagine an AVL tree with a path $(u_0, u_1, \ldots, u_k)$ where u_0 is the root and u_i is a child of u_{i-1}. We have 3 conditions:
(a) Let $i \geq 1$. Then u_i is a left child iff i is odd, and otherwise u_i is a right child. Thus, the path is a pure zigzag path.
(b) The height of u_i is $k - i$ (for $i = 0, \ldots, k$). Thus u_k is a leaf.
(c) Finally, the height of the sibling of u_i is $h - i - 1$.

Suppose we are trying to insert a key whose search path in the AVL tree is precisely $(u_0, \ldots, u_k)$. Can we preemptively balance the AVL tree in this case? ♢

END EXERCISES

§7. (a,b)-Search Trees

We consider another class of trees that is important in practice, especially in database applications. These are no longer binary trees, but are parametrized by a choice of two integers,

$$2 \leq a < b. \tag{7}$$

An (a,b)-**tree** is a rooted, ordered tree with the following requirements:

- DEPTH BOUND: All leaves are at the same depth.
- BRANCHING BOUND: Let m be the number of children of an internal node u. In general, we have the bounds
$$a \leq m \leq b. \tag{8}$$
The root is an exception, with the bound $2 \leq m \leq b$.

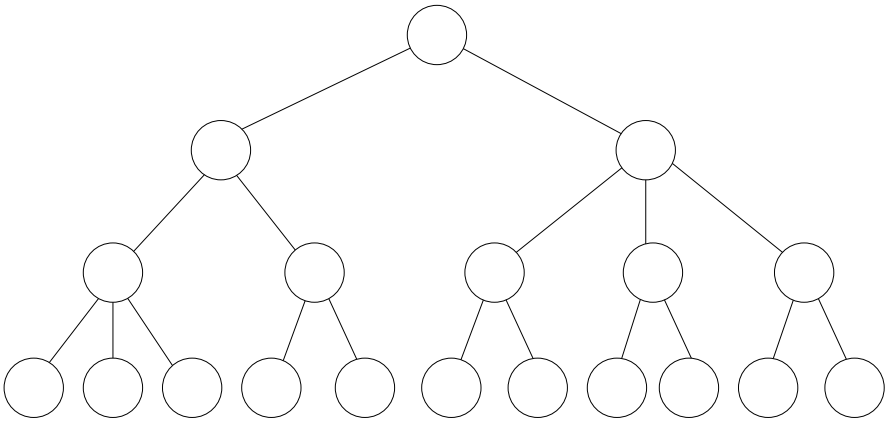


Figure 19: A $(2,3)$-tree.

To see the intuition behind these conditions, compare with binary trees. In binary trees, the leaves do not have to be at the same depth. To re-introduce some flexibility into trees where leaves have the same depth, we allow the number of children of an internal node to vary over a larger range $[a, b]$. Moreover, in order to ensure logarithmic height, we require $a \geq 2$. This means that if there n leaves, the height is at most $\log_a(n) + \mathcal{O}(1)$. Therefore, (a, b)-trees forms a balanced family of trees.

The definition of (a, b)-trees imposes purely structural requirements. Figure 19 illustrates an (a, b)-tree for $(a, b) = (2, 3)$. But to use (a, b)-trees as a search structure, we need to store keys and items in the nodes of the trees. These keys and items must be suitably organized. Before giving these details, we can build some intuition by studying an example of such a search tree in Figure 20. The 14 items stored in this tree are all at the leaves, with the keys $2, 4, 6, \ldots, 23, 25, 27$. As usual, we do not display the associated data in items. The keys in the internal nodes do not correspond to items.

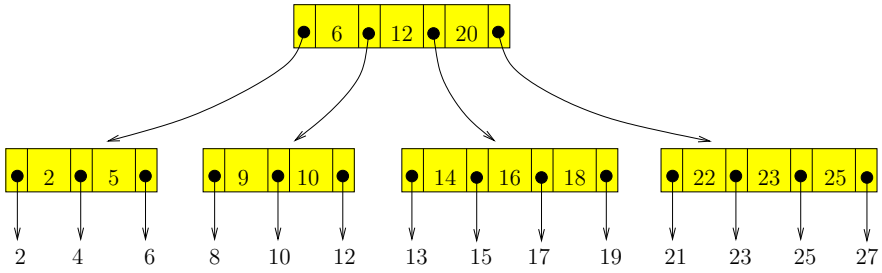


Figure 20: A (3,4)-search tree on 14 items

Recall that an item is a $(\texttt{key}, \texttt{data})$ pair. We define an (a, b)**-search tree** to be an (a, b)-tree whose nodes are organized as follows:

- LEAF: Each leaf stores a sequence of items, sorted by their keys. Hence we represent a leaf u with m items as the sequence,

$$u = (k_1, d_1, k_2, d_2, \ldots, k_m, d_m) \tag{9}$$

  where (k_i, d_i) is the ith smallest item. See Figure 21(i). In practice, d_i might only be a pointer to the actual location of the data. We must consider two cases. **NON-ROOT CASE:** suppose leaf u is not the root. In this case, we require

$$a' \leq m \leq b' \tag{10}$$

  for some $1 \leq a' \leq b'$. Here, (a', b') is an additional pair of parameters that are independent of (a, b). For simplicity, we will use $a' = b' = 1$ in our illustrations. **ROOT CASE:** suppose u is the root. Our requirements are relaxed somewhat to: $0 \leq m \leq 2b' - 1$. The reason for this condition will become clear when we discuss the insertion/deletion algorithms.

- INTERNAL NODE: Each internal node with m children stores an alternating sequence of keys and pointers (node references), in the form:

$$u = (p_1, k_1, p_2, k_2, p_3, \ldots, p_{m-1}, k_{m-1}, p_m) \tag{11}$$

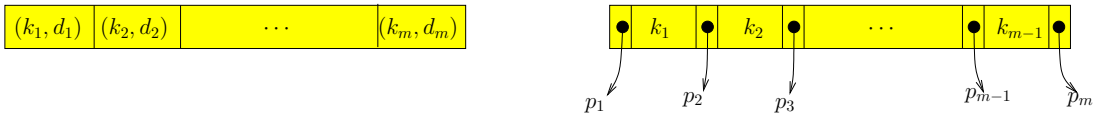
  where p_i is a pointer (or reference) to the i-th child of the current node. Note that the number of keys in this sequence is one less than the number m of children. See Figure 21(ii). The keys are sorted so that

$$k_1 < k_1 < \cdots < k_{m-1}.$$

  For $i = 1, \ldots, m$, each key k in the i-th subtree of u satisfies

$$k_{i-1} \leq k < k_i, \tag{12}$$

with the convention that $k_0 = -\infty < k_i < k_m = +\infty$. Note that this is just a generalization of the binary search tree property in (1).



$1 \le a' \le m \le b'$

(i) Leaf Node Organization

$2 \le a \le m \le b$

(ii) Internal Node Organization

Figure 21: Organization of nodes in (a,b)-search trees

¶37. Choice of the (a',b') parameters. Since the a', b' parameters are independent of a, b, it is convenient to choose some default value for our discussion of (a,b) trees. This decision is justified because the the dependence of our algorithms on the a', b' parameters are not significant (and they play roles analogous to a, b). There are two canonical choices: the simplest is $a' = b' = 1$. This means each leaf stores exactly one item. All our examples (e.g., Figure 20) use this default choice. Another canonical and perhaps more realistic choice is

So (a', b') is implicit!

$$a' = a, \quad b' = b. \tag{13}$$

As usual, we assume that the set of items in an (a,b)-search tree has unique keys. But as seen in Figure 20, the keys in internal nodes may be the same as keys in the leaves.

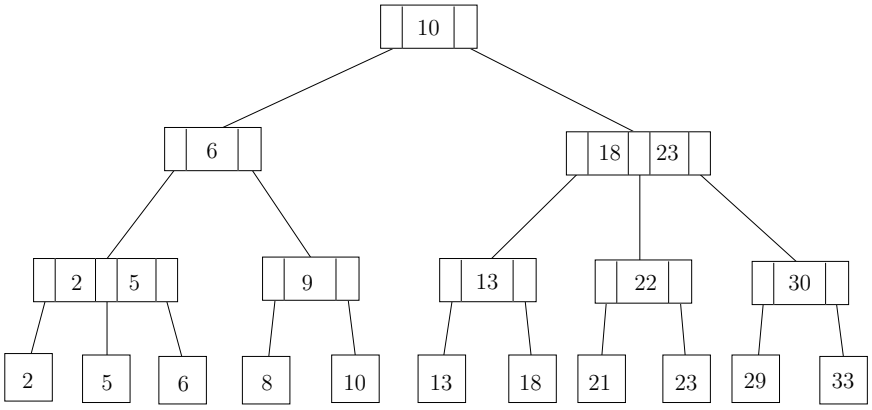


Figure 22: A $(2,3)$-search tree.

Another (a,b)-search tree is shown in Figure 22, for the case $(a,b) = (2,3)$. In contrast to Figure 20, here we use a slightly more standard convention of representing the pointers as tree edges.

¶38. Special Cases of (a,b)-Search Trees. The earliest and simplest (a,b)-search trees correspond to the case $(a,b) = (2,3)$. These are called **2-3 trees** and were introduced by Hopcroft (1970). By choosing

$$b = 2a - 1 \tag{14}$$

(for any $a \geq 2$), we obtain the generalization of $(2,3)$-trees called **B-trees**. These were introduced by McCreight and Bayer [2]. When $(a,b) = (2,4)$, the trees have been studied by Bayer (1972) as **symmetric binary B-trees** and by Guibas and Sedgewick as **2-3-4 trees**. Another variant of 2-3-4 trees is **red-black trees**. The latter can be viewed as an efficient way to implement 2-3-4 trees, by embedding them in binary search trees. But the price of this efficiency is complicated algorithms for insertion and deletion. Thus it is clear that the concept of (a,b)-search trees serves to unify a variety of search trees. The terminology of (a,b)-trees was used by Mehlhorn [7].

The B-tree relationship (14) is optimal in a certain[9] sense. Nevertheless, there are other benefits in allowing more general relationships between a and b. E.g., if we replace (14) by $b = 2a$, the amortized complexity of such (a,b)-search trees algorithms can improve [3].

¶39. Searching. The organization of an (a,b)-search tree supports an obvious lookup algorithm that is a generalization of binary search. Namely, to do `lookUp(key` k), we begin with the root as the current node. In general, if u is the current node, we process it as follows, depending on whether it is a leaf or not:

- Base Case: suppose u is a leaf node given by (9). If k occurs in u as k_i (for some $i = 1, \ldots, m$), then we return the associated data d_i. Otherwise, we return the null value, signifying search failure.
- Inductive Case: suppose u is an internal node given by (11). Then we find the p_i such that $k_{i-1} \leq k < k_i$ (with $k_0 = -\infty, k_m = \infty$). Set p_i as the new current node, and continue by processing the new current node.

The running time of the `lookUp` algorithm is $O(hb)$ where h is the height of the (a,b)-tree, and we spend $O(b)$ time at each node. The following bounds the height of (a,b)-trees:

LEMMA 6. *An (a,b)-tree with n leaves has height satisfying*

$$\lceil \log_b \lceil n/b' \rceil \rceil \leq h \leq 1 + \lfloor \log_a \lfloor n/(2a') \rfloor \rfloor . \tag{15}$$

Proof. The number ℓ of leaves clearly lies in the range $[\lfloor n/b' \rfloor , \lceil n/a' \rceil]$. However, with a little thought, we can improve it to:

$$\ell \in [\lceil n/b' \rceil , \lfloor n/a' \rfloor].$$

(Why?) With height h, we must have at least $2a^{h-1}$ leaves. Hence $\lfloor n/a' \rfloor \geq \ell \geq 2a^{h-1}$ or $\lfloor n/a' \rfloor /2 \geq a^{h-1}$. Since a^{h-1} is integer, we obtain $\lfloor \lfloor n/a' \rfloor /2 \rfloor = \lfloor n/(2a') \rfloor \geq a^{h-1}$ or $h \leq 1 + \log_a(\lfloor n/(2a') \rfloor)$. Again, since h is integer, this yields $h \leq 1 + \lfloor \log_a(\lfloor n/(2a') \rfloor) \rfloor$. For the lower bound on h, a similar (but simpler) argument holds. **Q.E.D.**

This lemma implies

$$\lceil \log_b \lceil n/b' \rceil \rceil \leq 1 + \lfloor \log_a \lfloor n/(2a') \rfloor \rfloor . \tag{16}$$

For instance, with $n = 10^9$ (a billion), $(a,b) = (34,51)$ and $a' = b' = 1$, this inequality is actually an equality (both sides are equal to 6). It become a strict inequality for n sufficiently large. For small n, the inequality may even fail. Hence it is clear that we need additional inequalities on our parameters.

This lemma shows that b, b' determine the lower bound and a, a' determine the upper bound on h. Our design goal is to maximize a, b, a', b' for speed, and to minimize b/a for space efficiency (see below). Typically b/a is bounded by a small constant close to 2, as in B-trees.

[9] I.e., assuming a certain type of split-merge inequality, which we will discuss below.

¶40. Organization within a node. The keys in a node of an (a,b)-tree must be ordered for searching, and manipulation such as merging or splitting two list of keys. Conceptually, we display them as in (11) and (9). Since the number of keys is not necessarily a small constant, the organization of these keys is an issue. In practice, b is a medium size constant (say, $b < 1000$) and a is a constant fraction of b. These ordered list of keys can be stored as an array, a singly- or doubly-linked list, or even as a balanced search tree. These have their usual trade-offs. With an array or balanced search tree at each node, the time spent at a node improves from $O(b)$ to $O(\log b)$. But a balanced search tree takes up more space than using a plain array organization; this will reduce the value of b. Hence, a practical compromise is to simply store the list as an array in each node. This achieves $O(\lg b)$ search time but each insertion and deletion in that node requires $O(b)$ time. When we take into account the effects of secondary memory, the time for searching within a node is negligible compared to the time accessing each node. This argues that the overriding goal in the design of (a,b)-search trees should be to maximize b and a.

The central tenet of (a,b)-trees!

¶41. The Standard Split and Merge Inequalities for (a,b)-trees. To support efficient insertion and deletion algorithms, the parameters a, b must satisfy an additional inequality in addition to (7). This inequality, which we now derive, comes from two low-level operations on (a,b)-search tree. These **split** and **merge** operations are called as subroutines by the insertion and deletion algorithms (respectively). There is actually a family of such inequalities, but we first derive the simplest one ("the standard inequality").

During insertion, a node with b children may acquire a new child. Such a node violates the requirements of an (a,b)-tree, so an obvious response is to **split** it into two nodes with $\lfloor (b+1)/2 \rfloor$ and $\lceil (b+1)/2 \rceil$ children, respectively. In order that the result is an (a,b)-tree, we require the following split inequality:

$$a \leq \left\lfloor \frac{b+1}{2} \right\rfloor . \tag{17}$$

Similarly, during deletion, we may remove a child from a node that has a children. The resulting node with $a-1$ children violates the requirements of an (a,b)-tree. So we may consider borrowing a child from one of its **siblings** (there may be one or two siblings), provided the sibling has more than a children. If this proves impossible, we are forced to **merge** a node with $a-1$ children with a node with a children. The resulting node has $2a-1$ children, and to satisfy the branching factor bound of (a,b)-trees, we have $2a-1 \leq b$. Thus we require the following merge inequality:

$$a \leq \frac{b+1}{2}. \tag{18}$$

Clearly (17) implies (18). However, since a and b are integers, the reverse implication also holds! Thus (17) and (18) are equivalent. The smallest choices of these parameters under the inequalities and also (7) is $(a,b) = (2,3)$, which has been mentioned above. The case of equality in (17) and (18) gives us $b = 2a-1$, which leads to precisely the B-trees. Sometimes, the condition $b = 2a$ is used to define B-trees; this behaves better in an amortized sense (see [7, Chap. III.5.3.1]).

¶42. How to Split, Borrow, and Merge. First, we discuss the *general case* of internal nodes that are non-root. The special case of leaves and root will be discussed later.

Suppose we need to split because an insertion into causes a node N to have $b+1$ children. This is illustrated in Figure 23. We split N into two new nodes N_1, N_2, one node with $\lfloor (b+1)/2 \rfloor$ pointers and the other with $\lceil (b+1)/2 \rceil$ pointers. The parent of N will replace its pointer to N with two pointers to N_1 and N_2. But what is the key to separate the pointers to N_1 and N_2? The solution is to use a key from N: there are b keys in the original node, but only $b-1$ will be needed by the two new nodes. The extra key can be moved in the parent node as indicated.

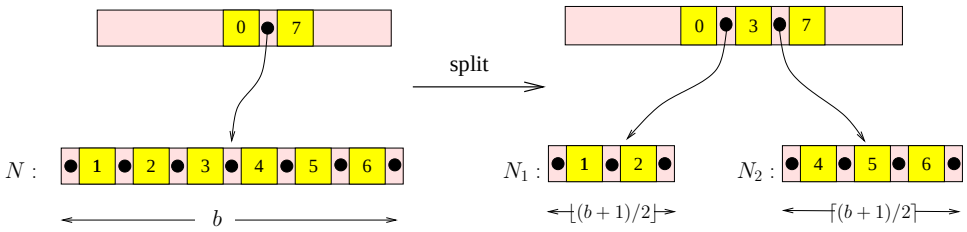


Figure 23: Splitting: N splits into N_1, N_1, $(a,b) = (3,6)$ illustrated

Next, suppose a deletion causes a N node to have $a-1$ children. First we try to borrow from a sibling if possible. This is because after borrowing, the rebalancing process can stop. To borrow, we look to a sibling (left or right), provided the sibling has more than a children. This is illustrated in Figure 24. Suppose N borrows a new from its sibling M. After borrowing, N will have a children, but it will need a key to separate the new pointer from its adjacent pointer. This key is taken from its parent node. Since M lost a child, it will have an extra key to spare — this can be sent to its parent node.

Do not borrow from a cousin or distant cousins. Why?

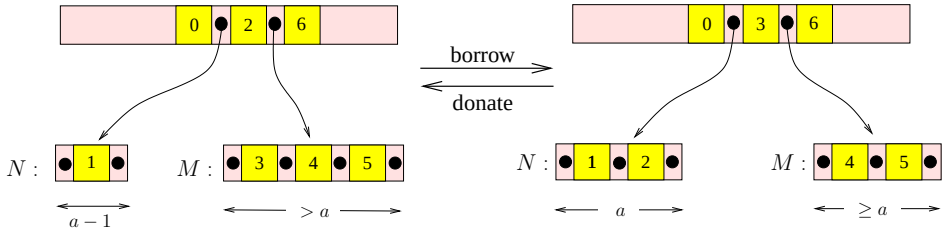


Figure 24: Borrowing: N borrows from M, $(a,b) = (3,6)$ illustrated

If N is unable to borrow, we resort to merging: let M be a sibling of N. Clearly M has a children, and so we can merge M and N into a new node N' with $2a-1$ children. Note that N' needs an extra key to separate the pointers of N from those of M. This key can be taken from the parent node; the parent node will not miss the loss because it has lost one child pointer in the merge. This is illustrated in Figure 25.

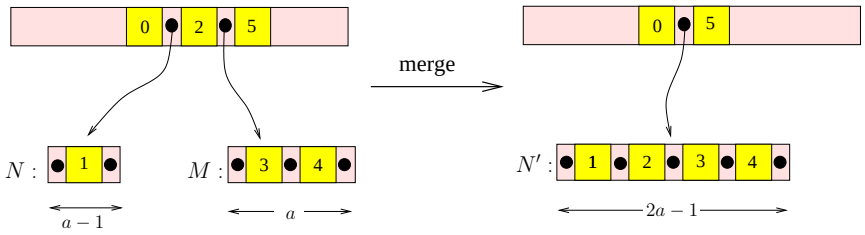


Figure 25: Merging: N and M merges into N', $(a,b) = (3,6)$ illustrated

Once the above three basic operations are understood, we can have a general algorithm for insertion and deletion. This will be explained after we take care of one more detail — the case of roots and leaves.

The careful reader will notice an asymmetry in the above three processes. We have the concept of borrowing, but it as much sense to talk about its inverse operation, donation. Indeed, if we simply reverse the direction of transformation in Figure 24, we have the donation operation (node N donates a key to node M). Just as the operation of merging can sometimes be preempted by borrowing, the operation of

splitting can sometimes be preempted by donation! This is not usually discussed in algorithms in the literature. Below we will see the benefits of this.

¶43. Treatment of Leaves and Root. Consider splits at the root, and merges of children of the root:

(i) Normally, when we split a node u, its parent gets one extra child. But when u is the root, we create a new root with two children. This explains the exception we allow for roots to have between 2 and b children.

(ii) Normally, when we merge two siblings u and v, the parent loses a child. But when the parent is the root, the root may now have only one child. In this case, we delete the root and its sole child is now the root.

Note that (i) and (ii) are the *only* means for increasing and decreasing the height of the (a,b)-tree.

Now consider leaves: in order for the splits and merges of leaves to proceed as above, we need the analogue of the split-merge inequality,

$$a' \leq \frac{b'+1}{2}. \tag{19}$$

Finally, consider the case where the root is also a leaf. We cannot treat it like an ordinary leaf having between a' to b' items. Suppose the parameters a'_0, b'_0 control the minimum and maximum number of items in a leaf. Let us determine constraints of a'_0 and b'_0 (relative to a', b'). Initially, there may be no items in the root, so we must let $a'_0 = 0$. Also, when the number of items exceed b'_0, we must split into two or more children with at least a' items. The standard literature allows the root to have 2 children and this requires $2a' \leq b'_0 + 1$ (like the standard split-merge inequality). Hence we require $b'_0 \leq 2a' - 1$.

not $b'_0 \leq 2a'_0 - 1$

In practice, it seems better to allow the root to have a large degree than a small degree. Thus, we might even want distinguish between leaves that are non-roots and the very special case of a root that is simultaneously a leaf. Such alternative designs are explored in Exercises.

¶44. Mechanics of Insertion and Deletion. Both insertion and deletion can be described as a repeated application of the following while-loop:

▷ *INITIALIZATION*
To insert an item (k, d) or delete a key k, we first do a lookup on k.
Let u be the leaf where k is found.
Bring u into main memory and perform the indicated operation.
Call u the **current node**.
▷ *MAIN LOOP*
while u is overfull or underfull, do:
1. If u is root, handle as a special case and terminate.
2. Bring the parent v of u into main memory. ◁ *No need if caching is used*
3. Depending on the case, some siblings u_1, u_2, etc, of u may be brought into main memory.
4. Do the necessary transformations of u and its siblings and v in the main memory.
   ◁ *While in main memory, a node is allowed to to have more than b or less than a children*
   ◁ *We may have created a new node or deleted a node*
5. Write back into secondary memory all the children of v.
6. Make v our new current node (rename it as u) and repeat this loop.

Write the current node u to secondary memory and terminate.

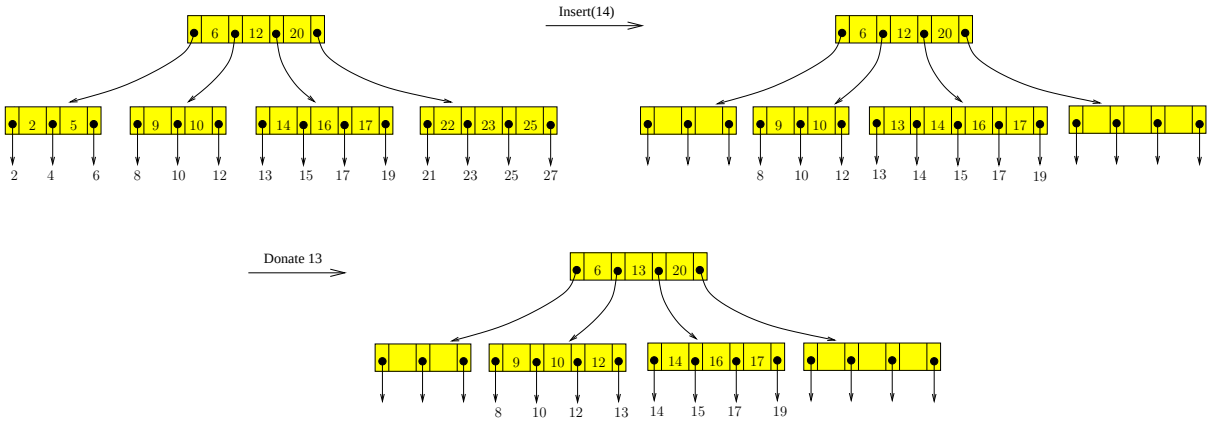


Figure 26: Inserting 14 into $(3, 4, 2)$-tree.

Insertion Example: Consider inserting the item (represented by its key) 14 into the tree in Figure 20. This is illustrated by Figure 26. Note that $a' = b' = 1$. After inserting 14, we get an overfull node with 5 children. Suppose we first try to donates to our left sibling. In this case, this is possible since the left sibling has less than 4 children.

But imagine that a slightly different algorithm which tries to first donate to the right sibling. In this case, the donation fails. Then our algorithm requires us to merge with the right sibling and then split into 3 nodes. Of course, it is also possible to imagine a variant where we try to donate to the left sibling if the right sibling is full. This variant may be slower since it involves bringing an additional disk I/O. The tradeoff is that it leads to better space utilization.

Deletion Example: Consider deleting the item (represented by its key) 4 from the tree in Figure 20. The is illustrated in Figure 27. After deleting 4, the current node u is underfull. We try to borrow from the right sibling, but failed. But the right sibling of the right sibling could give up one child.

One way to break down this process is to imagine that we merge u with the 2 siblings to its right (a 3-to-1 merge) to create supernode. This requires bringing some keys (6 and 12) from the parent of

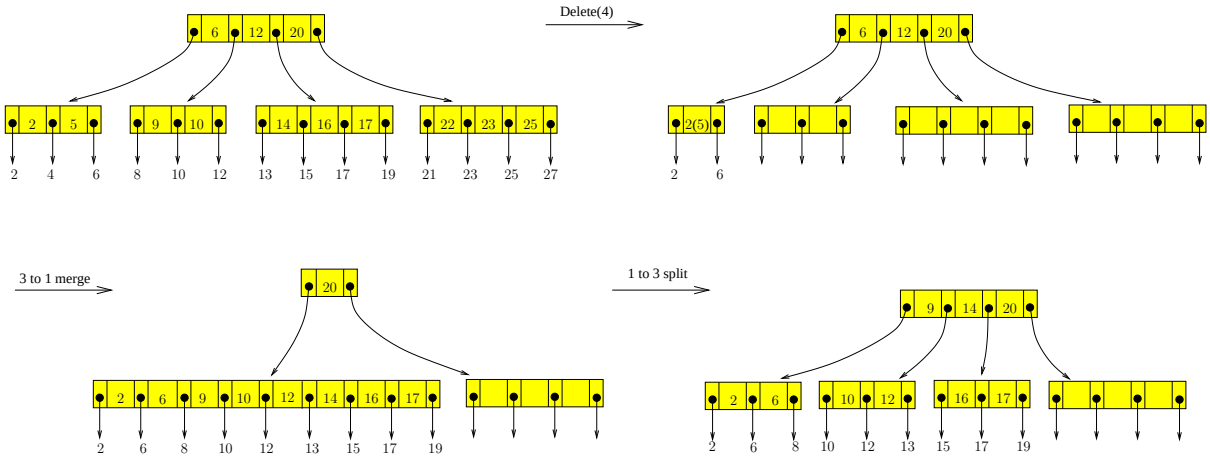


Figure 27: Deleting 4 from $(3,4,2)$-tree.

u into the supernode. The supernode has 9 children, which we can split evenly into 3 nodes (a 1-3 split). These nodes are inserted into the parent. Note that keys 9 and 14 are pushed into the parent. An implementation should be able combine this merge-then-split steps into one more efficient process.

¶45. Achieving $2/3$ Space Utility Ratio. A node with m children is said to be **full** when $m = b$; for in general, a node with m children is said to be (m/b)-**full**. Hence, nodes can be as small as (a/b)-full. Call the ratio $a : b$ the **space utilization ratio**. The standard inequality (18) on (a,b)-trees implies that the space utilization in such trees can never[10] be better than $\lfloor (b+1)/2 \rfloor / b$, and this can be achieved by B-trees. This ratio is as large as $2:3$ (achieved when $b = 3$), but as $b \to \infty$, it is asymptotically only slightly larger than $1:2$. We now address the issue of achieving ratios that are arbitrarily close to 1, for any choice of a, b. First, we show how to achieve $2/3$ asymptotically.

Consider the following modified insertion: to remove an **overfull** node u with $b+1$ children, we first look at a sibling v to see if we can **donate** a child to the sibling. If v is not full, we may donate to v. Otherwise, v is full and we can take the $2b+1$ children in u and v, and divide them into 3 groups as evenly as possible. So each group has between $\lfloor (2b+1)/3 \rfloor$ and $\lceil (2b+1)/3 \rceil$ keys. More precisely, the size of the three groups are

$$\lfloor (2b+1)/3 \rfloor, \quad \lfloor (2b+1)/3 \rceil, \quad \lceil (2b+1)/3 \rceil$$

where $\lfloor (2b+1)/3 \rceil$ denotes **rounding** to the nearest integer. Nodes u and v will (respectively) have one of these groups as their children, but the third group will be children of a new node. See Figure 28.

We want these groups to have between a and b children. The largest of these groups has at most b children (assuming $b \geq 2$). However, for the smallest of these groups to have at least a children, we require

$$a \leq \left\lfloor \frac{2b+1}{3} \right\rfloor . \tag{20}$$

This process of merging two nodes and splitting into three nodes is called **generalized split** because it involves merging as well as splitting. Let w be the parent of u and v. Thus, w will have an extra child v' after the generalized split. If w is now overfull, we have to repeat this process at w.

[10]The ratio $a : b$ is only an approximate measure of space utility for various reasons. First of all, it is an asymptotic limit as b grows. Furthermore, the relative sizes for keys and pointers also affect the space utilization. The ratio $a : b$ is a reasonable estimate only in case the keys and pointers have about the same size.

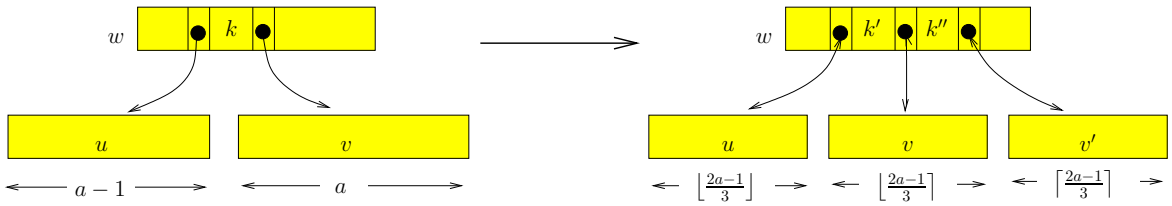


Figure 28: Generalized (2-to-3) split

Next consider a modified deletion: to remove an **underfull** node u with $a-1$ nodes, we again look at an adjacent sibling v to **borrow** a child. If v has a children, then we look at another sibling v' to borrow. If both attempts at borrowing fails, we merge the $3a-1$ children[11] the nodes u, v, v' and then split the result into two groups, as evenly as possible. Again, this is a **generalized merge** that involves a split as well. The sizes of the two groups are $\lfloor (3a-1)/2 \rfloor$ and $\lceil (3a-1)/2 \rceil$ children, respectively. Assuming

$$a \geq 3, \tag{21}$$

v and v' exists (unless u is a child of the root). This means

$$\left\lceil \frac{3a-1}{2} \right\rceil \leq b \tag{22}$$

Because of integrality constraints, the floor and ceiling symbols could be removed in both (20) and (22), without changing the relationship. And thus both inequality are seen to be equivalent to

$$a \leq \frac{2b+1}{3} \tag{23}$$

As in the standard (a,b)-trees, we need to make exceptions for the root. Here, the number m of children of the root satisfies the bound $2 \leq m \leq b$. So during deletion, the second sibling v' may not exist if u is a child of the root. In this case, we can simply merge the level 1 nodes, u and v. This merger is now the root, and it has $2a-1$ children. This suggests that we allow the root to have between a and $\max\{2a-1, b\}$ children.

> **Sharing with cousins?** In the above attempt to fix an overfull node u with $b+1$ children, we first try see to donate a child to a sibling v. Likewise, to fix an underfull node u with $a-1$ children, we first try to borrow a child from a sibling v. By definition, two nodes u, v are siblings of each other if v and u share a common parent w. Now, the children of w are linearly ordered $u_1 < u_2 < \cdots < u_m$ in a natural way, based on their keys. We say u_i, u_{i+1} are **direct siblings** for $i = 1, \ldots, m-1$. So each node u_i $(1 < i < m)$ has 2 direct siblings; but u_1 and u_m has only 1 direct sibling. It is important to realize that *a node can* **share** *(i.e., borrow or donate) with a direct sibling only.* In an Exercise, we consider a relaxed sharing condition, whereby sharing can be done between u and v if they are **direct cousins**.

If we view b as a hard constraint on the maximum number of children, then the only way to allow the root to have $\max\{2a-1, b\}$ children is to insist that $2a-1 \leq b$. Of course, this constraint is just the standard split-merge inequality (18); so we are back to square one. This says we must treat the root as an exception to the upper bound of b. Indeed, one can make a strong case for treating the root differently:

[11] Normally, we expect v, v' to be immediate siblings of u (to the left and right of u). But if u is the eldest or youngest sibling, then we may have to look slightly farther for the second sibling.

(1) It is desirable to keep the root resident in memory at all times, unlike the other nodes.
(2) Allow the root to be larger than b can speed up the general search.

The smallest example of a $(2/3)$-full tree is where $(a,b) = (3,4)$. We have already seen a $(3,4)$-tree in Figure 20. The nodes of such trees are actually $3/4$-full, not $2/3$-full. But for large b, the "$2/3$" estimate is more reasonable.

¶46. Exogenous and Endogenous Search Structures. Search trees store items. But where these items are stored constitute a major difference between (a,b)-search trees and the binary search trees which we have presented. Items in (a,b)-search trees are stored in the leaves only, while in binary search trees, items are stored in internal nodes as well. Tarjan [9, p. 9] calls a search structure **exogenous** if it stores items in leaves only; otherwise it is **endogenous**.

The keys in the internal nodes of (a,b)-search trees are used purely for searching: they are not associated with any data. In our description of binary search trees (or their balanced versions such as AVL trees), we never explicitly discuss the data that are associated with keys. So how do we know that these data structures are endogenous? We deduce it from the observation that, in looking up a key k in a binary search tree, if k is found in an internal node u, we stop the search and return u. Implicitly, it means we have found the item with key k (effectively, the item is stored in u). For (a,b)-search tree, we cannot stop at any internal node, but must proceed until we reach a leaf before we can conclude that an item with key k is, or is not, stored in the search tree. It is possible to modify binary search trees so that they become exogenous (Exercise).

There is another important consequence of this dual role of keys in (a,b)-search trees. The keys in the internal nodes *need not be the keys of items that are stored in the leaves*. This is seen in Figure 22 where the key 9 in an internal node does not correspond to any actual item in the tree. On the other hand, the key 13 appears in the leaves (as an item) as well as in an internal node.

Can't we require the keys in internal nodes to correspond to keys of stored items?

¶47. Database Application. One reason for treating (a,b)-trees as exogenous search structures comes from its applications in databases. In database terminology, (a,b)-search tree constitute an **index** over the set of items in its leaves. A given set of items can have more than one index built over it. If that is the case, at most one of the index can actually store the original data in the leaves. All the other indices must be contented to point to the original data, i.e., the d_i in (9) associated with key k_i is not the data itself, but a reference/pointer to the data stored elsewhere. Imagine a employee database where items are employee records. We may wish to create one index based on social security numbers, and another index based on last names, and yet another based on address. We chose these values (social security number, last name, address) for indexing because most searches in such a data base is presumably based on these values. It seems to make less sense to build an index based on age or salary, although we could.

¶48. Disk I/O Considerations: How to choose the parameter b. There is another reason for preferring exogenous structures. In databases, the number of items is very large and these are stored in disk memory. If there are n items, then we need at least n/b' internal nodes. This many internal nodes implies that the nodes of the (a,b)-trees is also stored in disk memory. Therefore, while searching through the (a,b)-tree, each node we visit must be brought into the main memory from disk. The I/O speed for transferring data between main memory and disk is relatively slow, compared to CPU speeds. Moreover, disk transfer at the lowest level of a computer organization takes place in fixed size **blocks** (or pages). E.g., in UNIX, block sizes are traditionally 512 bytes but can be as large as 16 Kbytes. To minimize the number of disk accesses, we want to pack as many keys into each node as possible. So the

ideal size for a node is the block size. Thus the parameter b of (a,b)-trees is chosen to be the largest value so that a node has this *b*lock size. Below, we discuss constraints on how the parameter a is chosen.

Parameter b is determined by block size

If the number of items stored in the (a,b)-tree is too many to be stored in main memory, the same would be true of the internal nodes of the (a,b)-tree. Hence each of these internal nodes are also stored on disk, and they are read into main memory as needed. Thus `lookUp`, `insert`and `delete` are known as **secondary memory algorithms** because data movement between disk and main memory must be explicitly invoked. Typically, it amounts to bringing a specific disk block into memory, or writing such a block back to disk.

¶49. On (a,b,c)-trees: Generalized Split-Merge for (a,b)-trees. Thus insertion and deletion algorithms uses the strategy of "share a key if you can" in order to avoid splitting or merging. Here, "sharing" encompasses borrowing as well as donation. The $2/3$-space utility method will now be generalized by the introduction of a new parameter $c \geq 1$. Call these (a,b,c)-**trees**. We use the parameter c as follows.

- **Generalized Split** of u: When node u is overfull, we will examine up to $c-1$ siblings to see if we can donate a child to these siblings. If so, we are done. Otherwise, we merge c nodes (node u plus $c-1$ siblings), and split the merger into $c+1$ nodes. We view c of these nodes as re-organizations of the original nodes, but one of them is regarded as new. We must insert this new node into the parent of u. The parent will be transformed appropriately.
- **Generalized Merge** of u: When node u is underfull, we will examine up to c siblings to see if we can borrow a child of these siblings. If so, we are done. Otherwise, we merge $c+1$ nodes (node u plus c siblings), and split the merger into c nodes. We view c of the original nodes as being re-organized, but one of them being deleted. We must thus delete a node from the parent of u. The parent will be transformed appropriately.

In summary, the generalized merge-split of (a,b,c)-trees transforms c nodes into $c+1$ nodes, or vice-versa. When $c=1$, we have the B-trees; when $c=2$, we achieve the $2/3$-space utilization ratio above. In general, they achieve a space utilization ratio of $c : c+1$ which can be arbitrarily close to 1 (we also need $b \to \infty$). Our (a,b,c)-trees must satisfy the following **generalized split-merge inequality**,

$$c+1 \leq a \leq \frac{cb+1}{c+1}. \tag{24}$$

The lower bound on a ensures that generalized merge or split of a node will always have enough siblings. In case of merging, the current node has $a-1$ keys. When we fail to borrow, it means that c siblings have a keys each. We can combine all these $a(c+1)-1$ keys and split them into c new nodes. This merging is valid because of the upper bound (24) on a. In case of splitting, the current node has $b+1$ keys. If we fail to donate, it means that $c-1$ siblings have b keys each. We combine all these $cb+1$ keys, and split them into $c+1$ new nodes. Again, the upper bound on a (24) guarantees success.

We are interested in the maximum value of a in (24). Using the fact that a is integer, this amounts to

$$a = \left\lfloor \frac{cb+1}{c+1} \right\rfloor. \tag{25}$$

The corresponding (a,b,c)-tree will be called a **generalized B-tree**. Thus generalized B-trees are specified by two parameters, b and c.

Example: What is the simplest generalized B-tree where $c=3$? Then $b > a \geq c+1 = 4$. So the smallest choices for these parameters are $(a,b,c) = (4,5,3)$.

¶50. Using the c parameter. An (a,b,c)-trees is structurally indistinguishable from an (a,b)-tree. In other words, the set of all (a,b,c) trees and the set of all (a,b) trees are the same ("co-extensive"). For any (a,b) parameter, we can compute the smallest c such that this could be a (a,b,c)-tree.

Therefore, we can freely modify the c as we wish. The c-parameter is only used during algorithm insertion/deletion, and this can be stored as a global variable. E.g., c can be a static member of the (a,b,c) class, if we implement this using C++). Why would we want to modify c? Increasing c improves space utilization but slows down the insertion/deletion process. Therefore, we can begin with $c = 1$, and as space becomes tight, we slowly increase c. And conversely we can decrease c as space becomes more available. This flexibility a great advantage of the c parameter.

¶51. A Numerical Example. Let us see how to choose the (a,b,c) parameters in a concrete setting. The nodes of the search tree are stored on the disk. The root is assumed to be always in main memory. To transfer data between disk and main memory, we assume a UNIX-like environment where memory blocks have size of 512 bytes. So that is the maximum size of each node. The reading or writing of one memory block constitute one disk access. Assume that each pointer is 4 bytes and each key 6 bytes. So each (key,pointer) pair uses 10 bytes. The value of b must satisfy $10b \leq 512$. Hence we choose $b = \lfloor 512/10 \rfloor = 51$. Suppose we want $c = 2$. In this case, the optimum choice of a is $a = \left\lfloor \frac{cb+1}{c+1} \right\rfloor = 34$.

To understand the speed of using such $(34, 51, 2)$-trees, assume that we store a billion items in such a tree. How many disk accesses in the worst is needed to lookup an item? The worst case is when the root has 2 children, and other internal nodes has 34 children (if possible). A calculation shows that the height is 6. Assume the root is in memory, we need only 6 block I/Os in the worst case. How many block accesses for insertion? We need to read c nodes and write out $c + 1$ nodes. For deletion, we need to read $c + 1$ nodes and write c nodes. In either case, we have $2c + 1$ nodes per level. With $c = 2$ and $h = 6$, we have a bound of 30 block accesses.

For storage requirement, let us bound the number of blocks needed to store the internal nodes of this tree. Let us assume each data item is 8 bytes (it is probably only a pointer). This allows us to compute the optimum value of a', b'. Thus $b' = \lfloor 512/8 \rfloor = 64$. Also, $a' = \left\lfloor \frac{cb'+1}{c+1} \right\rfloor = 43$. Using this, we can now calculate the maximum and number of blocks needed by our data structure (use Lemma 6).

¶52. Preemptive or 1-Pass Algorithms. The above algorithm uses 2-passes through nodes from the root to the leaf: one pass to go down the tree and another pass to go up the tree. There is a 1-pass versions of these algorithms. Such algorithms could potentially be twice as fast as the corresponding 2-pass algorithms since they could reduce the bottleneck disk I/O. The basic idea is to preemptively split (in case of insertion) or preemptively merge (in case of deletion).

More precisely, during insertion, if we find that the current node is already full (i.e., has b children) then it might be advisable to split u at this point. Splitting u will introduce a new child to its parent, v. We may assume that v is already in core, and by induction, v is not full. So v can accept a new child without splitting. In case of standard B-trees ($c = 1$), this involves no extra disk I/O. Such preemptive splits might turn out to be unnecessary, but this extra cost is negligible when the work is done in-core. Unfortunately, this is not true of generalized B-trees since a split requires looking at siblings which must be brought in from the disk. Further studies would be needed.

For deletion, we can again do a preemptive merge when the current node u has a children. Unfortunately, even for standard B-trees, this may involve extra disk I/O because we need to try to donate to a

sibling first.

But there is another intermediate solution: instead of preemptive merge/split, we simply **cache** the set of nodes from the root to the leaf. In this way, the second pass does not involve any disk I/O, unless absolutely necessary (when we need to split and/or merge). In modern computers, main memory is large and storing the entire path of nodes in the 2-pass algorithm seems to impose no burden. In this situation, the preemptive algorithms may actually be slower than a 2-pass algorithm with caching.

¶53. Background on Space Utilization. Using the $a : b$ measure, we see that standard B-trees have about 50% space utilization. Yao showed that in a random insertion model, the utilization is about $\lg 2 \sim 0.69\%$. (see [7]). This was the beginning of a technique called "fringe analysis" which Yao [10] introduced in 1974. Nakamura and Mizoguchi [8] independently discovered the analysis, and Knuth used similar ideas in 1973 (see the survey of [1]).

Now consider the space utilization ratio of generalized B-trees. Under (25), we see that the ratio $a : b$ is $\frac{cb+1}{(c+1)} : b$, and is greater than $c : c+1$. In case $c = 2$, our space utilization that is close to $\lg 2$. Unlike fringe analysis, we guarantee this utilization in the worst case. It seems that most of the benefits of (a, b, c)-trees are achieved with $c = 2$ or $c = 3$.

EXERCISES

Exercise 7.1: What is the the best ratio achievable under (18)? Under (23)? ♢

Exercise 7.2: Give a more detailed analysis of space utilization based on parameters for (A) a key value, (B) a pointer to a node, (C) either a pointer to an item (in the exogenous case) or the data itself (in the endogenous case). Suppose we need k bytes to store a key value, p bytes for a pointer to a node, and d bytes for a pointer to an item or for the data itself. Express the space utilization ratio in terms of the parameters

$$a, b, k, p, d$$

assuming the inequality (18). ♢

Exercise 7.3: Describe the exogenous version of binary search trees. Give the insertion and deletion algorithms. NOTE: the keys in the leaves are now viewed as surrogates for the items. Moreover, we allow the keys in the internal nodes to duplicate keys in the leaves, and it is also possible that some keys in the internal nodes correspond to no stored item. ♢

Exercise 7.4: Consider the tree shown in Figure 20. Although we previously viewed it as a $(3, 4)$-tree, we now want to view it as a $(2, 4)$-tree. For insertion/deletion we further treat it as a $(2, 4, 1)$-tree.
(a) Insert an item (whose key is) 14 into this tree. Draw intermediate results.
(b) Delete the item (whose key is) 4 from this tree. Draw intermediate results. ♢

Exercise 7.5: To understand the details of insertion and deletion algorithms in (a, b, c)-trees, we ask you to implement in your favorite language (we like Java) the following two $(2, 3, 1)$-trees and $(3, 4, 2)$-trees. ♢

Exercise 7.6: Is it possible to design (a, b, c) trees so that the root is not treated as an exception? ♢

Exercise 7.7: Suppose we want the root, if non-leaf, to have at least a children. But we now allow it to have more than b children. This is reasonably, considering that the root should probably be kept in memory all the time and so do not have to obey the b constraint. Here is the idea: we allow the root, when it is a leaf, to have up to $a'a - 1$ items. Here, (a', b') is the usual bound on the number of items in non-root leaves. Similarly, when it is a non-leaf, it has between a and $\max\{a^a - 1, b\}$ children. Show how to consistently carry out this policy. ♢

Exercise 7.8: Our insertion and deletion algorithms tries to share (i.e., donate or borrow) children from siblings only. Suppose we now relax this condition to allow sharing among "cousins". Consider all the nodes in a given level: two nodes nodes u, v are **cousins** of each other if they belong to the same level but they are not siblings. All the nodes v_i ($i = 1, \ldots, M$) in a given level can be sorted based on their keys, $v_1 < v_2 < \cdots < v_M$. If v_i, v_{i+1} are not siblings, then we call them **direct cousins**. Modify our insert/delete algorithms so that we try to share with direct siblings or cousins before doing the generalized split/merge. ♢

Exercise 7.9: We want to explore the weight balanced version of (a, b)-trees.
(a) Define such trees. Bound the heights of your weight-balanced $(a, b$-trees.
(b) Describe an insertion algorithm for your definition.
(c) Describe a deletion algorithm. ♢

Exercise 7.10: How can we choose the a parameter (see (25)) in generalized B-trees in a more relaxed manner so that the repeated splits/merges during insertion and deletions are minimized? ♢

END EXERCISES

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