Part III

Data Structures

Abstract Data Type

An abstract data type (ADT) is defined by an interface of operations or methods that can be performed and that have a defined behavior.

The data types in this lecture all operate on objects that are represented by a [key, value] pair.

- The key comes from a totally ordered set, and we assume that there is an efficient comparison function.
- The value can be anything; it usually carries satellite information important for the application that uses the ADT.

Dynamic Set Operations

- S. search(k): Returns pointer to object x from S with key[x] = k or null.
- S. insert(x): Inserts object x into set S. key[x] must not currently exist in the data-structure.
- S. delete(x): Given pointer to object x from S, delete x from the set.
- S. minimum(): Return pointer to object with smallest key-value in S.
- S. maximum(): Return pointer to object with largest key-value in S.
- S. successor(x): Return pointer to the next larger element in S or null if x is maximum.
- S. predecessor(x): Return pointer to the next smaller element in S or null if x is minimum.

- S. union(S'): Sets S := S \cup S'. The set S' is destroyed.
- S. merge(S'): Sets S := S \cup S'. Requires S \cap S' = \ø.
- S. split(k, S'):
  \[ S := \{ x \in S \mid \text{key}[x] \leq k \}, S' := \{ x \in S \mid \text{key}[x] > k \}. \]
- S. concatenate(S'): S := S \cup S'. Requires key[S. maximum()] \leq key[S'. minimum()].
- S. decrease-key(x, k): Replace key[x] by k \leq key[x].
Examples of ADTs

Stack:
- S. push(x): Insert an element.
- S. pop(): Return the element from S that was inserted most recently; delete it from S.
- S. empty(): Tell if S contains any object.

Queue:
- S. enqueue(x): Insert an element.
- S. dequeue(): Return the element that is longest in the structure; delete it from S.
- S. empty(): Tell if S contains any object.

Priority-Queue:
- S. insert(x): Insert an element.
- S. delete-min(): Return the element with lowest key-value; delete it from S.

Dictionary:

Dictionary:
- S. insert(x): Insert an element x.
- S. delete(x): Delete the element pointed to by x.
- S. search(k): Return a pointer to an element e with key[e] = k in S if it exists; otherwise return null.

7.1 Binary Search Trees

An (internal) binary search tree stores the elements in a binary tree. Each tree-node corresponds to an element. All elements in the left sub-tree of a node v have a smaller key-value than key[v] and elements in the right sub-tree have a larger-key value. We assume that all key-values are different.

(External Search Trees store objects only at leaf-vertices)

Examples:

We consider the following operations on binary search trees. Note that this is a super-set of the dictionary-operations.
- T. insert(x)
- T. delete(x)
- T. search(k)
- T. successor(x)
- T. predecessor(x)
- T. minimum()
- T. maximum()
Algorithm 1: TreeSearch(x, k)
- 1: if x = null or k = key[x] return x
- 2: if k < key[x] return TreeSearch(left[x], k)
- 3: else return TreeSearch(right[x], k)

Algorithm 2: TreeMin(x)
- 1: if x = null or left[x] = null return x
- 2: return TreeMin(left[x])

Algorithm 7: TreeSucc(x)
- 1: if right[x] ≠ null return TreeMin(right[x])
- 2: y ← parent[x]
- 3: while y ≠ null and x = right[y] do
- 4: x ← y; y ← parent[x]
- 5: return y;

Binary Search Trees: Searching

Binary Search Trees: Minimum

Binary Search Trees: Successor

Algorithm 1
1: if x = null or k = key[x] return x
2: if k < key[x] return TreeSearch(left[x], k)
3: else return TreeSearch(right[x], k)

Algorithm 2
1: if x = null or left[x] = null return x
2: return TreeMin(left[x])

Algorithm 7
1: if right[x] ≠ null return TreeMin(right[x])
2: y ← parent[x]
3: while y ≠ null and x = right[y] do
4: x ← y; y ← parent[x]
5: return y;
Algorithm 7 \text{TreeSucc}(x)
\begin{align*}
1: & \text{if right}_x \neq \text{null} \text{ return } \text{TreeMin(right}_x) \\
2: & y \leftarrow \text{parent}_x \\
3: & \text{while } y \neq \text{null} \text{ and } x = \text{right}_y \text{ do} \\
4: & \quad x \leftarrow y; y \leftarrow \text{parent}_x \\
5: & \text{return } y;
\end{align*}

Case 1:
Element does not have any children
- Simply go to the parent and set the corresponding pointer to \text{null}.

Case 2:
Element has exactly one child
- Splice the element out of the tree by connecting its parent to its successor.
Algorithm 9 TreeDelete(z)
1: if left[z] = null or right[z] = null
then y’ ← z
else y’ ← TreeSucc(z);
select y’ to splice out
2: if left[y] ≠ null
then x ← left[y] else x ← right[y];
3: if x ≠ null then
parent[x] ← parent[y];
4: if parent[y] = null then
5: root[T] ← x
6: else
7: left[parent[y]] ← x
8: if y = left[parent[y]] then
9: left[parent[y]] ← x
10: else
11: right[parent[y]] ← x
12: if y ≠ z then
13: copy y’-data to z

Case 3:
Element has two children
- Find the successor of the element
- Splice successor out of the tree
- Replace content of element by content of successor

Balanced Binary Search Trees
All operations on a binary search tree can be performed in time $O(h)$, where $h$ denotes the height of the tree.

However the height of the tree may become as large as $\Theta(n)$.

Balanced Binary Search Trees
With each insert- and delete-operation perform local adjustments to guarantee a height of $O(\log n)$.

AVL-trees, Red-black trees, Scapegoat trees, 2-3 trees, B-trees, AA trees, Treaps
similar: SPLAY trees.
7.2 Red Black Trees

Definition 1
A red black tree is a balanced binary search tree in which each internal node has two children. Each internal node has a color, such that
1. The root is black.
2. All leaf nodes are black.
3. For each node, all paths to descendant leaves contain the same number of black nodes.
4. If a node is red then both its children are black.

The null-pointers in a binary search tree are replaced by pointers to special null-vertices, that do not carry any object-data.

Red Black Trees: Example

7.2 Red Black Trees

Lemma 2
A red-black tree with \( n \) internal nodes has height at most \( \mathcal{O}(\log n) \).

Definition 3
The black height \( bh(v) \) of a node \( v \) in a red black tree is the number of black nodes on a path from \( v \) to a leaf vertex (not counting \( v \)).

We first show:

Lemma 4
A sub-tree of black height \( bh(v) \) in a red black tree contains at least \( 2^{bh(v)} - 1 \) internal vertices.

Proof of Lemma 4.
Induction on the height of \( v \).

base case (height(\( v \)) = 0)
- If height(\( v \)) (maximum distance btw. \( v \) and a node in the sub-tree rooted at \( v \)) is 0 then \( v \) is a leaf.
- The black height of \( v \) is 0.
- The sub-tree rooted at \( v \) contains \( 0 = 2^{bh(v)} - 1 \) inner vertices.
Proof (cont.)

induction step
▶ Suppose \( v \) is a node with \( \text{height}(v) > 0 \).
▶ \( v \) has two children with strictly smaller height.
▶ These children \((c_1, c_2)\) either have \( \text{bh}(c_i) = \text{bh}(v) \) or \( \text{bh}(c_i) = \text{bh}(v) - 1 \).
▶ By induction hypothesis both sub-trees contain at least \( 2^{\text{bh}(v)-1} - 1 \) internal vertices.
▶ Then \( T_v \) contains at least \( 2(2^{\text{bh}(v)-1} - 1) + 1 \geq 2^{\text{bh}(v)} - 1 \) vertices.

Proof of Lemma 2.

Let \( h \) denote the height of the red-black tree, and let \( P \) denote a path from the root to the furthest leaf.

At least half of the node on \( P \) must be black, since a red node must be followed by a black node.

Hence, the black height of the root is at least \( h/2 \).

The tree contains at least \( 2^{h/2} - 1 \) internal vertices. Hence, \( 2^{h/2} - 1 \leq n \).

Hence, \( h \leq 2 \log(n + 1) = O(\log n) \).

Definition 1

A red black tree is a balanced binary search tree in which each internal node has two children. Each internal node has a color, such that
1. The root is black.
2. All leaf nodes are black.
3. For each node, all paths to descendant leaves contain the same number of black nodes.
4. If a node is red then both its children are black.

The null-pointers in a binary search tree are replaced by pointers to special null-vertices, that do not carry any object-data.

We need to adapt the insert and delete operations so that the red black properties are maintained.
Rotations

The properties will be maintained through rotations:

```
  A
  |
  B
  |
  C
```

LeftRotate(x)

```
  A
  |
  B
  |
  C
```

RightRotate(z)

```
  A
  |
  B
  |
  C
```

Red Black Trees: Insert

Invariant of the fix-up algorithm:
- z is a red node
- the black-height property is fulfilled at every node
- the only violation of red-black properties occurs at z and parent[z]
  - either both of them are red (most important case)
  - or the parent does not exist (violation since root must be black)

If z has a parent but no grand-parent we could simply color the parent/root black; however this case never happens.

```
  18
  |
  13
  |
  25
```

Insert:
- first make a normal insert into a binary search tree
- then fix red-black properties

Red Black Trees: Insert

```
Algorithm 10 InsertFix(z)
1: while parent[z] ≠ null and col[parent[z]] = red do
2:   if parent[z] = left[gp[z]] then z in left subtree of grandparent
3:     uncle ← right[grandparent[z]]
4:     if col[uncle] = red then Case 1: uncle red
5:       col[p[z]] ← black; col[u] ← black;
6:       col[gp[z]] ← red; z ← grandparent[z];
7:     else Case 2: uncle black
8:       if z = right[parent[z]] then 2a: z right child
9:         Z ← p[z]; LeftRotate(z);
10:      col[p[z]] ← black; col[gp[z]] ← red; 2b: z left child
11:      RightRotate(gp[z]);
12:     else same as then-clause but right and left exchanged
13:   col(root[T]) ← black;
```
Case 1: Red Uncle

1. recolour
2. move $z$ to grand-parent
3. invariant is fulfilled for new $z$
4. you made progress

Case 2a: Black uncle and $z$ is right child

1. rotate around parent
2. move $z$ downwards
3. you have Case 2b.

Case 2b: Black uncle and $z$ is left child

1. rotate around grandparent
2. re-colour to ensure that black height property holds
3. you have a red black tree

Red Black Trees: Insert

Running time:
- Only Case 1 may repeat; but only $h/2$ many steps, where $h$ is the height of the tree.
- Case 2a $\rightarrow$ Case 2b $\rightarrow$ red-black tree
- Case 2b $\rightarrow$ red-black tree

Performing Case 1 at most $O(\log n)$ times and every other case at most once, we get a red-black tree. Hence $O(\log n)$ re-colorings and at most 2 rotations.
Red Black Trees: Delete

First do a standard delete.

If the spliced out node \( x \) was red everything is fine.

If it was black there may be the following problems.
- Parent and child of \( x \) were red; two adjacent red vertices.
- If you delete the root, the root may now be red.
- Every path from an ancestor of \( x \) to a descendant leaf of \( x \) changes the number of black nodes. Black height property might be violated.

Case 3:
Element has two children
- do normal delete
- when replacing content by content of successor, don’t change color of node

Delete:
- deleting black node messes up black-height property
- if \( z \) is red, we can simply color it black and everything is fine
- the problem is if \( z \) is black (e.g. a dummy-leaf); we call a fix-up procedure to fix the problem.

Invariant of the fix-up algorithm
- the node \( z \) is black
- if we “assign” a fake black unit to the edge from \( z \) to its parent then the black-height property is fulfilled

Goal: make rotations in such a way that you at some point can remove the fake black unit from the edge.
Case 1: Sibling of z is red

1. left-rotate around parent of z
2. recolor nodes $b$ and $c$
3. the new sibling is black (and parent of z is red)
4. Case 2 (special), or Case 3, or Case 4

Case 2: Sibling is black with two black children

1. re-color node $c$
2. move fake black unit upwards
3. move z upwards
4. we made progress
5. if $b$ is red we color it black and are done

Case 3: Sibling black with one black child to the right

1. do a right-rotation at sibling
2. recolor $c$ and $d$
3. new sibling is black with red right child (Case 4)

Case 4: Sibling is black with red right child

1. left-rotate around $b$
2. remove the fake black unit
3. recolor nodes $b$, $c$, and $e$
4. you have a valid red black tree
Running time:
- only Case 2 can repeat; but only $h$ many steps, where $h$ is the height of the tree
- Case 1 $\rightarrow$ Case 2 (special) $\rightarrow$ red black tree
  Case 1 $\rightarrow$ Case 3 $\rightarrow$ Case 4 $\rightarrow$ red black tree
  Case 1 $\rightarrow$ Case 4 $\rightarrow$ red black tree
- Case 3 $\rightarrow$ Case 4 $\rightarrow$ red black tree
- Case 4 $\rightarrow$ red black tree

Performing Case 2 at most $O(\log n)$ times and every other step at most once, we get a red black tree. Hence, $O(\log n)$ re-colorings and at most 3 rotations.

Red-Black Trees

Bibliography

Red black trees are covered in detail in Chapter 13 of [CLRS90].

Splay Trees

Disadvantage of balanced search trees:
- worst case; no advantage for easy inputs
- additional memory required
- complicated implementation

Splay Trees:
+ after access, an element is moved to the root; splay($x$)
  repeated accesses are faster
- only amortized guarantee
- read-operations change the tree

find($x$)
- search for $x$ according to a search tree
- let $\bar{x}$ be last element on search-path
- splay($\bar{x}$)
Splay Trees

**insert**(*x*)
- search for *x*; *x* is last visited element during search (successor or predecessor of *x*)
- splay(*x*) moves *x* to the root
- insert *x* as new root

**Splay Trees**

**delete**(*x*)
- search for *x*; splay(*x*); remove *x*
- search largest element *x* in *A*
- splay(*x*) (on subtree *A*)
- connect root of *B* as right child of *x*

**Move to Root**

How to bring element to root?
- one (bad) option: moveToRoot(*x*)
- iteratively do rotation around parent of *x* until *x* is root
- if *x* is left child do right rotation otw. left rotation

**Splay: Zig Case**

better option splay(*x*):
- zig case: if *x* is child of root do left rotation or right rotation around parent
**Splay: Zigzag Case**

Better option splay($x$):
- Zigzag case: if $x$ is right child and parent of $x$ is left child (or $x$ left child, parent of $x$ right child)
- Do double right rotation around grand-parent (resp. double left rotation)

Note that moveToRoot($x$) does the same.

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**Splay: Zigzig Case**

Better option splay($x$):
- Zigzig case: if $x$ is left child and parent of $x$ is left child (or $x$ right child, parent of $x$ right child)
- Do right rotation around grand-parent followed by right rotation around parent (resp. left rotations)

This case is different between moveToRoot($x$) and splay($x$).
### Static Optimality

Suppose we have a sequence of $m$ find-operations. $\text{find}(x)$ appears $h_x$ times in this sequence.

The cost of a static search tree $T$ is:

$$\text{cost}(T) = m + \sum_x h_x \text{depth}_T(x)$$

The total cost for processing the sequence on a splay-tree is $O(\text{cost}(T_{\text{min}}))$, where $T_{\text{min}}$ is an optimal static search tree.

---

### Dynamic Optimality

Let $S$ be a sequence with $m$ find-operations.

Let $A$ be a data-structure based on a search tree:

- the cost for accessing element $x$ is $1 + \text{depth}(x)$;
- after accessing $x$ the tree may be re-arranged through rotations;

**Conjecture:**
A splay tree that only contains elements from $S$ has cost $O(\text{cost}(A,S))$, for processing $S$. 

---
Lemma 5
Splay Trees have an *amortized* running time of $O(\log n)$ for all operations.

Potential Method

Introduce a potential for the data structure.
- $\Phi(D_i)$ is the potential after the $i$-th operation.
- Amortized cost of the $i$-th operation is
  \begin{equation}
  \hat{c}_i = c_i + \Phi(D_i) - \Phi(D_{i-1}).
  \end{equation}
- Show that $\Phi(D_i) \geq \Phi(D_0)$.

Then
\begin{equation}
\sum_{i=1}^{k} c_i \leq \sum_{i=1}^{k} c_i + \Phi(D_k) - \Phi(D_0) = \sum_{i=1}^{k} \hat{c}_i
\end{equation}
This means the amortized costs can be used to derive a bound on the total cost.

Amortized Analysis

Definition 6
A data structure with operations $\text{op}_1(), \ldots, \text{op}_k()$ has amortized running times $t_1, \ldots, t_k$ for these operations if the following holds.

Suppose you are given a sequence of operations (starting with an empty data-structure) that operate on at most $n$ elements, and let $k_i$ denote the number of occurrences of $\text{op}_i()$ within this sequence. Then the actual running time must be at most $\sum_i k_i \cdot t_i(n)$.

Example: Stack

Stack
- $S.\ push()$
- $S.\ pop()$
  - $S.\ multipop(k)$: removes $k$ items from the stack. If the stack currently contains less than $k$ items it empties the stack.
  - The user has to ensure that pop and multipop do not generate an underflow.

Actual cost:
- $S.\ push()$: cost 1.
- $S.\ pop()$: cost 1.
- $S.\ multipop(k)$: cost $\min\{\text{size}, k\} = k$. 
**Example: Stack**

Use potential function $\Phi(S) =$ number of elements on the stack.

**Amortized cost:**
- $S.$ push(): cost
  $$\hat{C}_{\text{push}} = C_{\text{push}} + \Delta\Phi = 1 + 1 \leq 2 .$$
- $S.$ pop(): cost
  $$\hat{C}_{\text{pop}} = C_{\text{pop}} + \Delta\Phi = 1 - 1 \leq 0 .$$
- $S.$ multipop($k$): cost
  $$\hat{C}_{\text{mp}} = C_{\text{mp}} + \Delta\Phi = \min\{\text{size}, k\} - \min\{\text{size}, k\} \leq 0 .$$

**Example: Binary Counter**

Choose potential function $\Phi(x) = k$, where $k$ denotes the number of ones in the binary representation of $x$.

**Amortized cost:**
- Changing bit from 0 to 1:
  $$\hat{C}_{0 \rightarrow 1} = C_{0 \rightarrow 1} + \Delta\Phi = 1 + 1 \leq 2 .$$
- Changing bit from 1 to 0:
  $$\hat{C}_{1 \rightarrow 0} = C_{1 \rightarrow 0} + \Delta\Phi = 1 - 1 \leq 0 .$$
- Increment: Let $k$ denotes the number of consecutive ones in the least significant bit-positions. An increment involves $k$ ($1 \rightarrow 0$)-operations, and one ($0 \rightarrow 1$)-operation.

Hence, the amortized cost is $k\hat{C}_{1 \rightarrow 0} + \hat{C}_{0 \rightarrow 1} \leq 2$.

**Splay Trees**

potential function for splay trees:
- size $s(x) = |T_x|$
- rank $r(x) = \log_2(s(x))$
- $\Phi(T) = \sum_{v \in T} r(v)$

amortized cost = real cost + potential change

The cost is essentially the cost of the splay-operation, which is 1 plus the number of rotations.
Splay: Zig Case

\[ \Delta \Phi = r'(x) + r'(p) - r(x) - r(p) \]
\[ = r'(p) - r(x) \]
\[ \leq r'(x) - r(x) \]

\[ \text{cost}_{\text{zig}} \leq 1 + 3(r'(x) - r(x)) \]

Splay: Zigzig Case

\[ \Delta \Phi = r'(x) + r'(p) + r'(g) - r(x) - r(p) - r(g) \]
\[ = r'(p) + r'(g) - r(x) - r(p) \]
\[ \leq r'(x) + r'(g) - r(x) - r(x) \]
\[ = r'(x) + r'(g) + r(x) - 3r'(x) + 3r'(x) - r(x) - 2r(x) \]
\[ = -2r'(x) + r'(g) + r(x) + 3(r'(x) - r(x)) \]
\[ \leq -2 + 3(r'(x) - r(x)) \]
\[ \Rightarrow \text{cost}_{\text{zigzig}} \leq 3(r'(x) - r(x)) \]

Splay: Zigzag Case

\[ \frac{1}{2} (r(x) + r'(g) - 2r'(x)) \]
\[ = \frac{1}{2} \left( \log(s(x)) + \log(s'(g)) - 2 \log(s'(x)) \right) \]
\[ = \frac{1}{2} \log \left( \frac{s(x)}{s'(x)} \right) + \frac{1}{2} \log \left( \frac{s'(g)}{s'(x)} \right) \]
\[ \leq \log \left( \frac{1}{2} s(x) + \frac{1}{2} s'(g) \right) \leq \log \left( \frac{1}{2} \right) = -1 \]

The last inequality follows from next slide.

The last inequality holds because \( \log \) is a concave function.
Splay: Zigzag Case

\[
\frac{1}{2} (r'(p) + r'(g) - 2r'(x))
\]

\[
= \frac{1}{2} \left( \log(s'(p)) + \log(s'(g)) - 2 \log(s'(x)) \right)
\]

\[
\leq \log \left( \frac{1}{2} s'(p) + \frac{1}{2} s'(g) \right) \leq \log \left( \frac{1}{2} \right) = -1
\]

Amortized cost of the whole splay operation:

\[
\leq 1 + 1 + \sum_{\text{steps } t} 3(r_t(x) - r_{t-1}(x))
\]

\[
= 2 + r(\text{root}) - r_0(x)
\]

\[
\leq O(\log n)
\]

The first one is added due to the fact that so far for each step of a splay-operation we have only counted the number of rotations, but the cost is \(1 + \#\text{rotations}\).

The second one comes from the zig-operation. Note that we have at most one zig-operation during a splay.

7.3 Splay Trees 11. Apr. 2018
Ernst Mayr, Harald Räcke

7.4 Augmenting Data Structures

Suppose you want to develop a data structure with:

- **Insert(x)**: insert element \(x\).
- **Search(k)**: search for element with key \(k\).
- **Delete(x)**: delete element referenced by pointer \(x\).
- **find-by-rank(\ell)**: return the \(\ell\)-th element; return “error” if the data-structure contains less than \(\ell\) elements.

Augment an existing data-structure instead of developing a new one.

Bibliography

7.4 Augmenting Data Structures 11. Apr. 2018
Ernst Mayr, Harald Räcke
7.4 Augmenting Data Structures

How to augment a data-structure
1. choose an underlying data-structure
2. determine additional information to be stored in the underlying structure
3. verify/show how the additional information can be maintained for the basic modifying operations on the underlying structure.
4. develop the new operations

- Of course, the above steps heavily depend on each other. For example it makes no sense to choose additional information to be stored (Step 2), and later realize that either the information cannot be maintained efficiently (Step 3) or is not sufficient to support the new operations (Step 4).
- However, the above outline is a good way to describe/document a new data-structure.

Goal: Design a data-structure that supports insert, delete, search, and find-by-rank in time $O(\log n)$.

1. We choose a red-black tree as the underlying data-structure.
2. We store in each node $v$ the size of the sub-tree rooted at $v$.
3. We need to be able to update the size-field in each node without asymptotically affecting the running time of insert, delete, and search. We come back to this step later...

4. How does find-by-rank work?
   Find-by-rank($k$) = Select(root, $k$) with

   **Algorithm 11 Select($x, i$)**
   1: if $x \text{ null}$ then return error
   2: if left[$x$] $\text{ null}$ then $r \leftarrow \text{left}[x]. \text{size} + 1$ else $r \leftarrow 1$
   3: if $i = r$ then return $x$
   4: if $i < r$ then
   5: return Select(left[$x$], $i$
   6: else
   7: return Select(right[$x$], $i - r$

Find-by-rank:
- decide whether you have to proceed into the left or right sub-tree
- adjust the rank that you are searching for if you go right
7.4 Augmenting Data Structures

Goal: Design a data-structure that supports insert, delete, search, and find-by-rank in time $O(\log n)$.

3. How do we maintain information?

Search($k$): Nothing to do.

Insert($x$): When going down the search path increase the size field for each visited node. Maintain the size field during rotations.

Delete($x$): Directly after splicing out a node traverse the path from the spliced out node upwards, and decrease the size counter on every node on this path. Maintain the size field during rotations.

Rotations

The only operation during the fix-up procedure that alters the tree and requires an update of the size-field:

The nodes $x$ and $z$ are the only nodes changing their size-fields. The new size-fields can be computed locally from the size-fields of the children.

Augmenting Data Structures

Bibliography


See Chapter 14 of [CLRS90].

7.5 $(a, b)$-trees

Definition 7

For $b \geq 2a - 1$ an $(a, b)$-tree is a search tree with the following properties

1. all leaves have the same distance to the root
2. every internal non-root vertex $v$ has at least $a$ and at most $b$ children
3. the root has degree at least 2 if the tree is non-empty
4. the internal vertices do not contain data, but only keys (external search tree)
5. there is a special dummy leaf node with key-value $\infty$
Each internal node $v$ with $d(v)$ children stores $d - 1$ keys $k_1, \ldots, k_{d-1}$. The $i$-th subtree of $v$ fulfills

$$ k_{i-1} < \text{key in } i\text{-th sub-tree} \leq k_i, $$

where we use $k_0 = -\infty$ and $k_d = \infty$.


### Variants

- The dummy leaf element may not exist; it only makes implementation more convenient.
- Variants in which $b = 2a$ are commonly referred to as $B$-trees.
- A $B$-tree usually refers to the variant in which keys and data are stored at internal nodes.
- A $B^*$ tree stores the data only at leaf nodes as in our definition. Sometimes the leaf nodes are also connected in a linear list data structure to speed up the computation of successors and predecessors.
- A $B^*$ tree requires that a node is at least $2/3$-full as opposed to $1/2$-full (the requirement of a $B$-tree).
Search

Search(8)

The search is straightforward. It is only important that you need to go all the way to the leaf.

Time: \(O(b \cdot h) = O(b \cdot \log n)\), if the individual nodes are organized as linear lists.

Search(19)

The search is straightforward. It is only important that you need to go all the way to the leaf.

Time: \(O(b \cdot h) = O(b \cdot \log n)\), if the individual nodes are organized as linear lists.

Insert

Insert element \(x\):

- Follow the path as if searching for \(\text{key}[x]\).
- If this search ends in leaf \(\ell\), insert \(x\) before this leaf.
- For this add \(\text{key}[x]\) to the key-list of the last internal node \(v\) on the path.
- If after the insert \(v\) contains \(b\) nodes, do Rebalance(\(v\)).

Rebalance(\(v\)):

- Let \(k_i, i = 1, \ldots, b\) denote the keys stored in \(v\).
- Let \(j := \lceil \frac{b+1}{2} \rceil\) be the middle element.
- Create two nodes \(v_1\) and \(v_2\). \(v_1\) gets all keys \(k_1, \ldots, k_{j-1}\) and \(v_2\) gets keys \(k_{j+1}, \ldots, k_b\).
- Both nodes get at least \(\lceil \frac{b-1}{2} \rceil + 1 \geq a\) since \(b \geq 2a - 1\).
- They get at most \(\lceil \frac{b+1}{2} \rceil\) keys, and have therefore degree at most \(\lceil \frac{b-1}{2} \rceil + 1 \leq b\) (since \(b \geq 2\)).
- The key \(k_j\) is promoted to the parent of \(v\). The current pointer to \(v\) is altered to point to \(v_1\), and a new pointer (to the right of \(k_j\)) in the parent is added to point to \(v_2\).
- Then, re-balance the parent.
Delete

Delete element $x$ (pointer to leaf vertex):

- Let $v$ denote the parent of $x$. If $\text{key}[x]$ is contained in $v$, remove the key from $v$, and delete the leaf vertex.
- Otherwise delete the key of the predecessor of $x$ from $v$; delete the leaf vertex; and replace the occurrence of $\text{key}[x]$ in internal nodes by the predecessor key. (Note that it appears in exactly one internal vertex).
- If now the number of keys in $v$ is below $a - 1$ perform Rebalance$'(v)$.

Rebalance$'(v)$:

- If there is a neighbour of $v$ that has at least $a$ keys take over the largest (if right neighbor) or smallest (if left neighbour) and the corresponding sub-tree.
- If not: merge $v$ with one of its neighbours.
- The merged node contains at most $(a - 2) + (a - 1) + 1$ keys, and has therefore at most $2a - 1 \leq b$ successors.
- Then rebalance the parent.
- During this process the root may become empty. In this case the root is deleted and the height of the tree decreases.

(2, 4)-trees and red black trees

There is a close relation between red-black trees and (2, 4)-trees:

First make it into an internal search tree by moving the satellite-data from the leaves to internal nodes. Add dummy leaves.
There is a close relation between red-black trees and (2, 4)-trees:

Then, color one key in each internal node \( v \) black. If \( v \) contains 3 keys you need to select
the middle key otherwise choose a black key
arbitrarily. The other keys are colored red.

Then, re-attach the pointers to individual keys. A
pointer that is between two keys is attached as
a child of the red key. The incoming pointer,
points to the black key.

Note that this correspondence is not unique. In particular, there
are different red-black trees that correspond to the same
(2, 4)-tree.

Augmenting Data Structures

Bibliography

[KMS08] Kurt Mehlhorn, Peter Sanders:
Algorithms and Data Structures — The Basic Toolbox,
Springer, 2008

[CLRS90] Thomas H. Cormen, Charles E. Leiserson, Ron L. Rivest, Clifford Stein:
Introduction to algorithms (3rd ed.),
MIT Press and McGraw-Hill, 2009

A description of B-trees (a specific variant of \((a, b)\)-trees) can be found in Chapter 18 of [CLRS90].
Chapter 7.2 of [MS08] discusses \((a, b)\)-trees as discussed in the lecture.
7.6 Skip Lists

Why do we not use a list for implementing the ADT Dynamic Set?

- time for search $\Theta(n)$
- time for insert $\Theta(n)$ (dominated by searching the item)
- time for delete $\Theta(1)$ if we are given a handle to the object, otw. $\Theta(n)$

Add an express lane:

Let $|L_1|$ denote the number of elements in the “express lane”, and $|L_0| = n$ the number of all elements (ignoring dummy elements).

Worst case search time: $|L_1| + |L_0|$ (ignoring additive constants)

Choose $|L_1| = \sqrt{n}$. Then search time $\Theta(\sqrt{n})$.

Choose ratios between list-lengths evenly, i.e., $\frac{|L_i|}{|L_{i-1}|} = r$, and, hence, $L_k \approx r^{-k} n$.

Worst case running time is: $O(r^{-k} n + kr)$.

Choose $r = n^{\frac{1}{k+1}}$. Then

$$r^{-k} n + kr = \left(n^{\frac{1}{k+1}}\right)^{-k} n + kn^{\frac{1}{k+1}} = n^{1 - \frac{k}{k+1}} + kn^{\frac{1}{k+1}} = (k + 1)n^{\frac{1}{k+1}}.$$ 

Choosing $k = \Theta(\log n)$ gives a logarithmic running time.

Add more express lanes. Lane $L_i$ contains roughly every $\frac{L_{i+1}}{L_i}$-th item from list $L_{i-1}$.

Search(x) ($k + 1$ lists $L_0, \ldots, L_k$)

- Find the largest item in list $L_k$ that is smaller than $x$. At most $|L_k| + 2$ steps.
- Find the largest item in list $L_{k-1}$ that is smaller than $x$. At most $|L_{k-1}| + 2$ steps.
- Find the largest item in list $L_{k-2}$ that is smaller than $x$. At most $|L_{k-2}| + 2$ steps.
- ... 
- At most $|L_k| + \sum_{i=1}^{k} \frac{L_{i+1}}{L_i} + 3(k + 1)$ steps.
How to do insert and delete?

- If we want that in $L_i$ we always skip over roughly the same number of elements in $L_{i-1}$ an insert or delete may require a lot of re-organisation.

Use randomization instead!

Insert:
- A search operation gives you the insert position for element $x$ in every list.
- Flip a coin until it shows head, and record the number $t \in \{1, 2, \ldots\}$ of trials needed.
- Insert $x$ into lists $L_0, \ldots, L_{t-1}$.

Delete:
- You get all predecessors via backward pointers.
- Delete $x$ in all lists it actually appears in.

The time for both operations is dominated by the search time.

High Probability

Definition 10 (High Probability)
We say a randomized algorithm has running time $O(\log n)$ with high probability if for any constant $\alpha$ the running time is at most $O(\log n)$ with probability at least $1 - \frac{1}{n^\alpha}$.

Here the $O$-notation hides a constant that may depend on $\alpha$. 
High Probability

Suppose there are polynomially many events \( E_1, E_2, \ldots, E_\ell \), \( \ell = n^c \) each holding with high probability (e.g. \( E_i \) may be the event that the \( i \)-th search in a skip list takes time at most \( O(\log n) \)).

Then the probability that all \( E_i \) hold is at least

\[
\Pr[E_1 \land \cdots \land E_\ell] = 1 - \Pr[\bar{E}_1 \lor \cdots \lor \bar{E}_\ell] \\
\geq 1 - n^c \cdot n^{-\alpha} \\
= 1 - n^{c-\alpha}.
\]

This means \( \Pr[E_1 \land \cdots \land E_\ell] \) holds with high probability.

Lemma 11

A search (and, hence, also insert and delete) in a skip list with \( n \) elements takes time \( O(\log n) \) with high probability (w. h. p.).

7.6 Skip Lists

Backward analysis:

At each point the path goes up with probability \( 1/2 \) and left with probability \( 1/2 \).

We show that w.h.p:

- A “long” search path must also go very high.
- There are no elements in high lists.

From this it follows that w.h.p. there are no long paths.

\[
\left( \frac{n}{k} \right)^k \leq \left( \frac{n}{k} \right) \leq \left( \frac{en}{k} \right)^k
\]

\[
\left( \frac{n}{k} \right)^k = \frac{n!}{k! \cdot (n-k)!} = \frac{n \cdot \ldots \cdot (n-k+1)}{k \cdot \ldots \cdot 1} \geq \left( \frac{n}{k} \right)^k
\]

\[
\left( \frac{n}{k} \right)^k = \frac{n \cdot \ldots \cdot (n-k+1)}{k!} \leq \frac{n^k}{k!} = \frac{n^k \cdot k^k}{k! \cdot k!}
\]

\[
= \left( \frac{n}{k} \right)^k \cdot \frac{k^k}{k!} \leq \left( \frac{en}{k} \right)^k
\]
7.6 Skip Lists

Let $E_{z,k}$ denote the event that a search path is of length $z$ (number of edges) but does not visit a list above $L_k$.

In particular, this means that during the construction in the backward analysis we see at most $k$ heads (i.e., coin flips that tell you to go up) in $z$ trials.

So far we fixed $k = \gamma \log n$, $\gamma \geq 1$, and $z = 7\alpha \gamma \log n$, $\alpha \geq 1$.

This means that a search path of length $\Omega(\log n)$ visits a list on a level $\Omega(\log n)$, w.h.p.

Let $A_{k+1}$ denote the event that the list $L_{k+1}$ is non-empty. Then

$$\Pr[A_{k+1}] \leq n2^{-(k+1)} \leq n^{-(y-1)}.$$  

For the search to take at least $z = 7\alpha \gamma \log n$ steps either the event $E_{z,k}$ or the event $A_{k+1}$ must hold. Hence,

$$\Pr[\text{search requires } z \text{ steps}] \leq \Pr[E_{z,k}] + \Pr[A_{k+1}]$$

$$\leq n^{-\alpha} + n^{-(y-1)}$$

This means, the search requires at most $z$ steps, w.h.p.

Bibliography

[GT98] Michael T. Goodrich, Roberto Tamassia
Data Structures and Algorithms in JAVA
John Wiley, 1998

Skip lists are covered in Chapter 7.5 of [GT98].
7.7 Hashing

Dictionary:

- \textbf{S. insert}(x): Insert an element \(x\).
- \textbf{S. delete}(x): Delete the element pointed to by \(x\).
- \textbf{S. search}(k): Return a pointer to an element \(e\) with key[\(e\)] = \(k\) in \(S\) if it exists; otherwise return \texttt{null}.

So far we have implemented the search for a key by carefully choosing split-elements.

Then the memory location of an object \(x\) with key \(k\) is determined by successively comparing \(k\) to split-elements.

Hashing tries to \textit{directly} compute the memory location from the given key. The goal is to have constant search time.

Direct Addressing

Ideally the hash function maps \textit{all} keys to different memory locations.

This special case is known as \textit{Direct Addressing}. It is usually very unrealistic as the universe of keys typically is quite large, and in particular larger than the available memory.

Perfect Hashing

Suppose that we know the set \(S\) of actual keys (no insert/no delete). Then we may want to design a simple hash-function that maps all these keys to different memory locations.

Such a hash function \(h\) is called a \textit{perfect hash function} for set \(S\).
Collisions

If we do not know the keys in advance, the best we can hope for is that the hash function distributes keys evenly across the table.

Problem: Collisions

Usually the universe $U$ is much larger than the table-size $n$.

Hence, there may be two elements $k_1, k_2$ from the set $S$ that map to the same memory location (i.e., $h(k_1) = h(k_2)$). This is called a collision.

Typically, collisions do not appear once the size of the set $S$ of actual keys gets close to $n$, but already when $|S| \geq \omega(\sqrt{n})$.

Lemma 12

The probability of having a collision when hashing $m$ elements into a table of size $n$ under uniform hashing is at least

$$1 - e^{-\frac{m(m-1)}{2n}} \approx 1 - e^{-\frac{m^2}{2n}}.$$

Uniform hashing:

Choose a hash function uniformly at random from all functions $f : U \rightarrow [0, \ldots, n-1]$.

Proof.

Let $A_{m,n}$ denote the event that inserting $m$ keys into a table of size $n$ does not generate a collision. Then

$$\Pr[A_{m,n}] = \prod_{\ell=1}^{m} \frac{n - \ell + 1}{n} = \prod_{j=0}^{m-1} \left(1 - \frac{j}{n}\right) \leq \prod_{j=0}^{m-1} e^{-j/n} = e^{-\sum_{j=0}^{m-1} \frac{j}{n}} = e^{-\frac{m(m-1)}{2n}}.$$

Here the first equality follows since the $\ell$-th element that is hashed has a probability of $\frac{n - \ell + 1}{n}$ to not generate a collision under the condition that the previous elements did not induce collisions.

The inequality $1 - x \leq e^{-x}$ is derived by stopping the Taylor-expansion of $e^{-x}$ after the second term.
Resolving Collisions

The methods for dealing with collisions can be classified into the two main types

- open addressing, aka. closed hashing
- hashing with chaining, aka. closed addressing, open hashing.

There are applications e.g. computer chess where you do not resolve collisions at all.

Hashing with Chaining

Let $A$ denote a strategy for resolving collisions. We use the following notation:

- $A^+$ denotes the average time for a successful search when using $A$;
- $A^-$ denotes the average time for an unsuccessful search when using $A$;
- We parameterize the complexity results in terms of $\alpha := \frac{m}{n}$, the so-called fill factor of the hash-table.

We assume uniform hashing for the following analysis.
Hashing with Chaining

For a successful search observe that we do not choose a list at random, but we consider a random key \( k \) in the hash-table and ask for the search-time for \( k \).

This is 1 plus the number of elements that lie before \( k \) in \( k \)’s list.

Let \( k_\ell \) denote the \( \ell \)-th key inserted into the table.

Let for two keys \( k_i \) and \( k_j \), \( X_{ij} \) denote the indicator variable for the event that \( k_i \) and \( k_j \) hash to the same position. Clearly, \( \Pr[X_{ij} = 1] = \frac{1}{n} \) for uniform hashing.

The expected successful search cost is

\[
E \left[ \frac{1}{m} \sum_{i=1}^{m} \left( 1 + \sum_{j=i+1}^{m} X_{ij} \right) \right] = \frac{1}{m} \sum_{i=1}^{m} \left( 1 + \sum_{j=i+1}^{m} \frac{1}{n} \right) = 1 + \frac{1}{mn} \sum_{i=1}^{m} (m - i) = 1 + \frac{1}{mn} \left( m^2 - \frac{m(m+1)}{2} \right) = 1 + \frac{m - 1}{2n} = 1 + \frac{\alpha}{2} - \frac{\alpha}{2m}.
\]

Hence, the expected cost for a successful search is \( A^+ \leq 1 + \frac{\alpha}{2} \).

Disadvantages:
- pointers increase memory requirements
- pointers may lead to bad cache efficiency

Advantages:
- no à priori limit on the number of elements
- deletion can be implemented efficiently
- by using balanced trees instead of linked list one can also obtain worst-case guarantees.

Open Addressing

All objects are stored in the table itself.

Define a function \( h(k, j) \) that determines the table-position to be examined in the \( j \)-th step. The values \( h(k, 0), \ldots, h(k, n-1) \) must form a permutation of \( 0, \ldots, n-1 \).

Search(\( k \)): Try position \( h(k, 0) \); if it is empty your search fails; otw. continue with \( h(k, 1), h(k, 2), \ldots \).

Insert(\( x \)): Search until you find an empty slot; insert your element there. If your search reaches \( h(k, n-1) \), and this slot is non-empty then your table is full.
Open Addressing

Choices for $h(k,j)$:

- **Linear probing:**
  \[ h(k,i) = h(k) + i \mod n \]
  (sometimes: $h(k,i) = h(k) + ci \mod n$).

- **Quadratic probing:**
  \[ h(k,i) = h(k) + c_1 i + c_2 i^2 \mod n. \]

- **Double hashing:**
  \[ h(k,i) = h_1(k) + ih_2(k) \mod n. \]

For quadratic probing and double hashing one has to ensure that the search covers all positions in the table (i.e., for double hashing $h_2(k)$ must be relatively prime to $n$ (teilerfremd); for quadratic probing $c_1$ and $c_2$ have to be chosen carefully).

Linear Probing

- Advantage: **Cache-efficiency.** The new probe position is very likely to be in the cache.
- Disadvantage: **Primary clustering.** Long sequences of occupied table-positions get longer as they have a larger probability to be hit. Furthermore, they can merge forming larger sequences.

**Lemma 13**

Let $L$ be the method of linear probing for resolving collisions:

\[
L^+ \approx \frac{1}{2} \left( 1 + \frac{1}{1 - \alpha} \right)
\]
\[
L^- \approx \frac{1}{2} \left( 1 + \frac{1}{(1 - \alpha)^2} \right)
\]

Quadratic Probing

- Not as cache-efficient as Linear Probing.
- **Secondary clustering:** caused by the fact that all keys mapped to the same position have the same probe sequence.

**Lemma 14**

Let $Q$ be the method of quadratic probing for resolving collisions:

\[
Q^+ \approx 1 + \ln \left( \frac{1}{1 - \alpha} \right) - \frac{\alpha}{2}
\]
\[
Q^- \approx \frac{1}{1 - \alpha} + \ln \left( \frac{1}{1 - \alpha} \right) - \alpha
\]

Double Hashing

- Any probe into the hash-table usually creates a cache-miss.

**Lemma 15**

Let $A$ be the method of double hashing for resolving collisions:

\[
A^+ \approx \frac{1}{\alpha} \ln \left( \frac{1}{1 - \alpha} \right)
\]
\[
A^- \approx \frac{1}{1 - \alpha}
\]
Open Addressing

Some values:

<table>
<thead>
<tr>
<th>α</th>
<th>Linear Probing $L^+$</th>
<th>Quadratic Probing $Q^+$</th>
<th>Double Hashing $D^+$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>1.5</td>
<td>1.44</td>
<td>1.39</td>
</tr>
<tr>
<td>0.9</td>
<td>5.5</td>
<td>2.85</td>
<td>2.55</td>
</tr>
<tr>
<td>0.95</td>
<td>10.5</td>
<td>3.52</td>
<td>3.15</td>
</tr>
</tbody>
</table>

Analysis of Idealized Open Address Hashing

We analyze the time for a search in a very idealized Open Addressing scheme.

- The probe sequence $h(k, 0), h(k, 1), h(k, 2), \ldots$ is equally likely to be any permutation of $\langle 0, 1, \ldots, n-1 \rangle$.

Analysis of Idealized Open Address Hashing

Let $X$ denote a random variable describing the number of probes in an unsuccessful search.

Let $A_i$ denote the event that the $i$-th probe occurs and is to a non-empty slot.

$$\Pr[A_1 \cap A_2 \cap \ldots \cap A_{i-1}] = \Pr[A_1] \cdot \Pr[A_2 \mid A_1] \cdot \Pr[A_3 \mid A_1 \cap A_2] \cdot \ldots \cdot \Pr[A_{i-1} \mid A_1 \cap \ldots \cap A_{i-2}]$$

$$\Pr[X \geq i] = \frac{m}{n} \cdot \frac{m-1}{n-1} \cdot \frac{m-2}{n-2} \cdot \ldots \cdot \frac{m-i+2}{n-i+2} \leq \left( \frac{m}{n} \right)^{i-1} = \alpha^{i-1}.$$
Analysis of Idealized Open Address Hashing

\[ E[X] = \sum_{i=1}^{\infty} \Pr[X \geq i] \leq \sum_{i=1}^{\infty} \alpha^{i-1} = \sum_{i=0}^{\infty} \alpha^i = \frac{1}{1 - \alpha}. \]

\[ \frac{1}{1 - \alpha} = 1 + \alpha + \alpha^2 + \alpha^3 + \ldots \]

The \( j \)-th rectangle appears in both sums \( j \) times. (\( j \) times in the first due to multiplication with \( j \); and \( j \) times in the second for summands \( i = 1, 2, \ldots, j \))

Analysis of Idealized Open Address Hashing

**i = 3**

The number of probes in a successful search for \( k \) is equal to the number of probes made in an unsuccessful search for \( k \) at the time that \( k \) is inserted.

Let \( k \) be the \( i + 1 \)-st element. The expected time for a search for \( k \) is at most \( \frac{1}{1 - \frac{i}{n}} = \frac{n}{n - i} \).

\[ \frac{1}{m} \sum_{i=0}^{m-1} \frac{n}{n-i} = \frac{n}{m} \sum_{i=0}^{m-1} \frac{1}{n-i} = \frac{1}{\alpha} \sum_{k=n-m+1}^{n} \frac{1}{k} \leq \frac{1}{\alpha} \int_{n-m}^{n} \frac{1}{x} \, dx = \frac{1}{\alpha} \ln \frac{n}{n-m} = \frac{1}{\alpha} \ln \frac{1}{1 - \alpha}. \]
Deletions in Hashtables

- Simply removing a key might interrupt the probe sequence of other keys which then cannot be found anymore.
- One can delete an element by replacing it with a deleted-marker.
  - During an insertion if a deleted-marker is encountered an element can be inserted there.
  - During a search a deleted-marker must not be used to terminate the probe sequence.
- The table could fill up with deleted-markers leading to bad performance.
- If a table contains many deleted-markers (linear fraction of the keys) one can rehash the whole table and amortize the cost for this rehash against the cost for the deletions.

Deletions for Linear Probing

- For Linear Probing one can delete elements without using deletion-markers.
- Upon a deletion elements that are further down in the probe-sequence may be moved to guarantee that they are still found during a search.
Deletions for Linear Probing

Algorithm 12: \texttt{delete}(p)

1: \( T[p] \leftarrow \text{null} \)
2: \( p \leftarrow \text{succ}(p) \)
3: \textbf{while} \( T[p] \neq \text{null} \) \textbf{do}
4: \( y \leftarrow T[p] \)
5: \( T[p] \leftarrow \text{null} \)
6: \( p \leftarrow \text{succ}(p) \)
7: \texttt{insert}(y)

\( p \) is the index into the table-cell that contains the object to be deleted.

Pointers into the hash-table become invalid.

Universal Hashing

Regardless, of the choice of hash-function there is always an input (a set of keys) that has a very poor worst-case behaviour.

Therefore, so far we assumed that the hash-function is random so that regardless of the input the average case behaviour is good.

However, the assumption of uniform hashing that \( h \) is chosen randomly from all functions \( f: U \rightarrow \{0,\ldots,n-1\} \) is clearly unrealistic as there are \( n^{|U|} \) such functions. Even writing down such a function would take \( |U| \log n \) bits.

Universal hashing tries to define a set \( \mathcal{H} \) of functions that is much smaller but still leads to good average case behaviour when selecting a hash-function uniformly at random from \( \mathcal{H} \).

Universal Hashing

Definition 16

A class \( \mathcal{H} \) of hash-functions from the universe \( U \) into the set \( \{0,\ldots,n-1\} \) is called universal if for all \( u_1, u_2 \in U \) with \( u_1 \neq u_2 \)

\[
\Pr[h(u_1) = h(u_2)] \leq \frac{1}{n},
\]

where the probability is w.r.t. the choice of a random hash-function from set \( \mathcal{H} \).

Note that this means that the probability of a collision between two arbitrary elements is at most \( \frac{1}{n} \).

Definition 17

A class \( \mathcal{H} \) of hash-functions from the universe \( U \) into the set \( \{0,\ldots,n-1\} \) is called 2-independent (pairwise independent) if the following two conditions hold

\begin{itemize}
  \item For any key \( u \in U \), and \( t \in \{0,\ldots,n-1\} \) \( \Pr[h(u) = t] = \frac{1}{n} \), i.e., a key is distributed uniformly within the hash-table.
  \item For all \( u_1, u_2 \in U \) with \( u_1 \neq u_2 \), and for any two hash-positions \( t_1, t_2 \):
    \[
    \Pr[h(u_1) = t_1 \land h(u_2) = t_2] \leq \frac{1}{n^2}.
    \]
\end{itemize}

This requirement clearly implies a universal hash-function.
Universal Hashing

**Definition 18**
A class \( \mathcal{H} \) of hash-functions from the universe \( U \) into the set \( \{0, \ldots, n-1\} \) is called \( k \)-independent if for any choice of \( \ell \leq k \) distinct keys \( u_1, \ldots, u_\ell \in U \), and for any set of \( \ell \) not necessarily distinct hash-positions \( t_1, \ldots, t_\ell \):

\[
\Pr[h(u_1) = t_1 \land \cdots \land h(u_\ell) = t_\ell] \leq \frac{1}{n^\ell},
\]

where the probability is w. r. t. the choice of a random hash-function from set \( \mathcal{H} \).

**Lemma 20**
The class
\[ \mathcal{H} = \{ h_{a,b} \mid a \in \mathbb{Z}_p^*, b \in \mathbb{Z}_p \} \]
is a universal class of hash-functions from \( U \) to \( \{0, \ldots, n-1\} \).

**Proof.**
Let \( x, y \in U \) be two distinct keys. We have to show that the probability of a collision is only \( 1/n \).

\[ ax + b \not\equiv ay + b \pmod{p} \]

If \( x \neq y \) then \( (x - y) \not\equiv 0 \pmod{p} \).

Multiplying with \( a \not\equiv 0 \pmod{p} \) gives
\[ a(x - y) \not\equiv 0 \pmod{p} \]

where we use that \( \mathbb{Z}_p \) is a field (Körper) and, hence, has no zero divisors (nullteilerfrei).
The hash-function does not generate collisions before the \( (\text{mod } n) \)-operation. Furthermore, every choice \((a,b)\) is mapped to a different pair \((t_x,t_y)\) with \(t_x := ax + b\) and \(t_y := ay + b\).

This holds because we can compute \(a\) and \(b\) when given \(t_x\) and \(t_y\):

\[
\begin{align*}
t_x &\equiv ax + b \pmod{p} \\
t_y &\equiv ay + b \pmod{p} \\
t_x - t_y &\equiv a(x - y) \pmod{p} \\
a &\equiv (t_x - t_y)(x - y)^{-1} \pmod{p} \\
b &\equiv t_y - ay \pmod{p}
\end{align*}
\]

Therefore, we can view the first step (before the \( \text{mod } n \)-operation) as choosing a pair \((t_x,t_y)\), \(t_x \neq t_y\) uniformly at random.

What happens when we do the \( \text{mod } n \) operation?

Fix a value \(t_x\). There are \(p - 1\) possible values for choosing \(t_y\).

From the range \(0,\ldots,p-1\) the values \(t_x, t_x + n, t_x + 2n, \ldots\) map to \(t_x\) after the modulo-operation. These are at most \(\lceil p/n \rceil\) values.

As \(t_y \neq t_x\) there are

\[
\left\lfloor \frac{p}{n} \right\rfloor - 1 \leq \frac{p}{n} + \frac{n-1}{n} - 1 \leq \frac{p-1}{n}
\]

possibilities for choosing \(t_y\) such that the final hash-value creates a collision.

This happens with probability at most \(\frac{1}{n}\).

It is also possible to show that \(H\) is an (almost) pairwise independent class of hash-functions.

\[
\frac{\left\lfloor \frac{p}{n} \right\rfloor^2}{p(p-1)} \leq \Pr_{t_x \neq t_y \in \mathbb{Z}_p} \left[ t_x \mod n = h_1 \wedge t_y \mod n = h_2 \right] \leq \frac{\left\lceil \frac{p}{n} \right\rceil^2}{p(p-1)}
\]

Note that the middle is the probability that \(h(x) = h_1\) and \(h(y) = h_2\). The total number of choices for \((t_x,t_y)\) is \(p(p-1)\).

The number of choices for \(t_x\) \((t_y)\) such that \(t_x \mod n = h_1\) \((t_y \mod n = h_2)\) lies between \(\left\lfloor \frac{p}{n} \right\rfloor\) and \(\left\lceil \frac{p}{n} \right\rceil\).
Universal Hashing

**Definition 21**

Let $d \in \mathbb{N}$; $q \geq (d + 1)n$ be a prime; and let $\vec{a} \in \{0, \ldots, q - 1\}^{d+1}$. Define for $x \in \{0, \ldots, q - 1\}$

$$h_{\vec{a}}(x) := \left( \sum_{i=0}^{d} a_i x^i \mod q \right) \mod n .$$

Let $\mathcal{H}_n^d := \{h_{\vec{a}} | \vec{a} \in \{0, \ldots, q - 1\}^{d+1}\}$. The class $\mathcal{H}_n^d$ is $(e, d + 1)$-independent.

Note that in the previous case we had $d = 1$ and chose $a_d \neq 0$.

---

Universal Hashing

Fix $\ell \leq d + 1$; let $x_1, \ldots, x_\ell \in \{0, \ldots, q - 1\}$ be keys, and let $t_1, \ldots, t_\ell$ denote the corresponding hash-function values.

Let $A^\ell = \{h_{\vec{a}} \in \mathcal{H} | h_{\vec{a}}(x_i) = t_i \text{ for all } i \in \{1, \ldots, \ell\}\}$

Then

$$h_{\vec{a}} \in A^\ell \Leftrightarrow h_{\vec{a}} = f_{\vec{a}} \mod n$$

$$f_{\vec{a}}(x_i) \in \{t_i + \alpha \cdot n | \alpha \in \{0, \ldots, \left\lfloor \frac{q}{n} \right\rfloor - 1\}\} =: B_i$$

In order to obtain the cardinality of $A^\ell$ we choose our polynomial by fixing $d + 1$ points.

We first fix the values for inputs $x_1, \ldots, x_\ell$.

We have

$$|B_1| \cdots \cdot |B_\ell|$$

possibilities to do this (so that $h_{\vec{a}}(x_i) = t_i$).

---

Universal Hashing

For the coefficients $\vec{a} \in \{0, \ldots, q - 1\}^{d+1}$ let $f_{\vec{a}}$ denote the polynomial

$$f_{\vec{a}}(x) = \left( \sum_{i=0}^{d} a_i x^i \right) \mod q$$

The polynomial is defined by $d + 1$ distinct points.

Now, we choose $d - \ell + 1$ other inputs and choose their value arbitrarily. We have $q^{d-\ell+1}$ possibilities to do this.

Therefore we have

$$|B_1| \cdots \cdot |B_\ell| \cdot q^{d-\ell+1} \leq \left\lfloor \frac{q}{n} \right\rfloor \ell \cdot q^{d-\ell+1}$$

possibilities to choose $\vec{a}$ such that $h_{\vec{a}} \in A^\ell$.
Universal Hashing

Therefore the probability of choosing $h_a$ from $A_\ell$ is only

$$\frac{\left(\frac{q+n}{n}\right)^\ell}{\left(\frac{q}{q}\right)^\ell \cdot \frac{1}{n^\ell}} \leq \left(1 + \frac{1}{\ell}\right) \cdot \frac{1}{n^\ell} \leq \frac{e}{n^\ell}.$$  

This shows that the $H$ is $(e, d + 1)$-universal.

The last step followed from $q \geq (d + 1)n$, and $\ell \leq d + 1$.

Perfect Hashing

Suppose that we know the set $S$ of actual keys (no insert/no delete). Then we may want to design a simple hash-function that maps all these keys to different memory locations.

Let $m = |S|$. We could simply choose the hash-table size very large so that we don’t get any collisions.

Using a universal hash-function the expected number of collisions is

$$E[\#\text{Collisions}] = \left(\frac{m}{2}\right) \cdot \frac{1}{n}.$$  

If we choose $n = m^2$ the expected number of collisions is strictly less than $\frac{1}{2}$.

Can we get an upper bound on the probability of having collisions?

The probability of having 1 or more collisions can be at most $\frac{1}{2}$ as otherwise the expectation would be larger than $\frac{1}{2}$.

Perfect Hashing

We can find such a hash-function by a few trials.

However, a hash-table size of $n = m^2$ is very very high.

We construct a two-level scheme. We first use a hash-function that maps elements from $S$ to $m$ buckets.

Let $m_j$ denote the number of items that are hashed to the $j$-th bucket. For each bucket we choose a second hash-function that maps the elements of the bucket into a table of size $m_j^2$. The second function can be chosen such that all elements are mapped to different locations.
**Perfect Hashing**

The total memory that is required by all hash-tables is $O(\sum_j m_j^2)$. Note that $m_j$ is a random variable.

$$E\left[\sum_j m_j^2\right] = E\left[2\sum_j \left(\frac{m_j}{2}\right) + \sum_j m_j\right]$$

$$= 2E\left[\sum_j \left(\frac{m_j}{2}\right)^2\right] + E\left[\sum_j m_j\right]$$

The first expectation is simply the expected number of collisions, for the first level. Since we use universal hashing we have

$$= 2\left(\frac{m}{2}\right) \frac{1}{m} + m = 2m - 1.$$ 

**Cuckoo Hashing**

**Goal:**

Try to generate a hash-table with constant worst-case search time in a dynamic scenario.

- Two hash-tables $T_1[0,\ldots,n-1]$ and $T_2[0,\ldots,n-1]$, with hash-functions $h_1$, and $h_2$.
- An object $x$ is either stored at location $T_1[h_1(x)]$ or $T_2[h_2(x)]$.
- A search clearly takes constant time if the above constraint is met.

We need only $O(m)$ time to construct a hash-function $h$ with $\sum_j m_j^2 = O(4m)$, because with probability at least 1/2 a random function from a universal family will have this property.

Then we construct a hash-table $h_j$ for every bucket. This takes expected time $O(m_j)$ for every bucket. A random function $h_j$ is collision-free with probability at least 1/2. We need $O(m_j)$ to test this.

We only need that the hash-functions are chosen from a universal family!!!
Cuckoo Hashing

Insert:

We call one iteration through the while-loop a \textit{step} of the algorithm.

We call a sequence of iterations through the while-loop without the termination condition becoming true a \textit{phase} of the algorithm.

We say a phase is \textit{successful} if it is not terminated by the \texttt{maxstep}-condition, but the while loop is left because \( x = \text{null} \).

What is the expected time for an insert-operation?

We first analyze the probability that we end-up in an infinite loop (that is then terminated after \( \texttt{maxsteps} \) steps).

Formally what is the probability to enter an infinite loop that touches \( s \) different keys?
Cuckoo Hashing: Insert

A cycle-structure is active if for every key $x_\ell$ (linking a cell $p_i$ from $T_1$ and a cell $p_j$ from $T_2$) we have

$$h_1(x_\ell) = p_i \quad \text{and} \quad h_2(x_\ell) = p_j$$

Observation:
If during a phase the insert-procedure runs into a cycle there must exist an active cycle structure of size $s \geq 3$.

Cuckoo Hashing

A cycle-structure of size $s$ is defined by

- $s - 1$ different cells (alternating btw. cells from $T_1$ and $T_2$).
- $s$ distinct keys $x = x_1, x_2, \ldots, x_s$, linking the cells.
- The leftmost cell is “linked forward” to some cell on the right.
- The rightmost cell is “linked backward” to a cell on the left.
- One link represents key $x$; this is where the counting starts.

What is the probability that all keys in a cycle-structure of size $s$ correctly map into their $T_1$-cell?

This probability is at most $\mu n^s$ since $h_1$ is a $(\mu, s)$-independent hash-function.

What is the probability that all keys in the cycle-structure of size $s$ correctly map into their $T_2$-cell?

This probability is at most $\mu n^s$ since $h_2$ is a $(\mu, s)$-independent hash-function.

These events are independent.
Cuckoo Hashing

The probability that a given cycle-structure of size $s$ is active is at most $\frac{\mu^2 n^2}{m^2}$.

What is the probability that there exists an active cycle structure of size $s$?

The number of cycle-structures of size $s$ is at most $s^3 \cdot n^{s-1} \cdot m^{s-1}$.

- There are at most $s^2$ possibilities where to attach the forward and backward links.
- There are at most $s$ possibilities to choose where to place key $x$.
- There are $m^{s-1}$ possibilities to choose the keys apart from $x$.
- There are $n^{s-1}$ possibilities to choose the cells.

Now, we analyze the probability that a phase is not successful without running into a closed cycle.

The probability that there exists an active cycle-structure is therefore at most

$$\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2 n^2}{m^2} = \frac{\mu^2}{m^2} \sum_{s=3}^{\infty} s^3 \left( \frac{m}{n} \right)^s \leq \frac{\mu^2}{m^2} \sum_{s=3}^{\infty} s^3 \left( \frac{1}{1+\epsilon} \right)^s \leq O \left( \frac{1}{m^2} \right).$$

Here we used the fact that $(1+\epsilon)m \leq n$.

Hence,

$$\text{Pr}[\text{cycle}] = O \left( \frac{1}{m^2} \right).$$
Consider the sequence of not necessarily distinct keys starting with \( x \) in the order that they are visited during the phase.

**Lemma 22**

If the sequence is of length \( p \) then there exists a sub-sequence of at least \( \frac{p+2}{3} \) keys starting with \( x \) of distinct keys.

**Proof.**

Let \( i \) be the number of keys (including \( x \)) that we see before the first repeated key. Let \( j \) denote the total number of distinct keys.

The sequence is of the form:

\[
x = x_1 \rightarrow x_2 \rightarrow \cdots \rightarrow x_i \rightarrow x_r \rightarrow x_{r-1} \rightarrow \cdots \rightarrow x_1 \rightarrow x_{i+1} \rightarrow \cdots \rightarrow x_j
\]

As \( r \leq i - 1 \) the length \( p \) of the sequence is

\[
p = i + r + (j - i) \leq i + j - 1.
\]

Either sub-sequence \( x_1 \rightarrow x_2 \rightarrow \cdots \rightarrow x_i \) or sub-sequence \( x_1 \rightarrow x_{i+1} \rightarrow \cdots \rightarrow x_j \) has at least \( \frac{p+2}{3} \) elements. \( \Box \)
Cuckoo Hashing

A path-structure is active if for every key \( x \ell \) (linking a cell \( p_i \) from \( T_1 \) and a cell \( p_j \) from \( T_2 \)) we have\[ h_1(x) = p_i \quad \text{and} \quad h_2(x) = p_j. \]

Observation:
If a phase takes at least \( t \) steps without running into a cycle there must exist an active path-structure of size \( \left( \frac{2t}{3} + \frac{2}{3} \right) \).

Note that we count complete steps. A search that touches \( 2t \) or \( 2t + 1 \) keys takes \( t \) steps.

7.7 Hashing 11. Apr. 2018
Ernst Mayr, Harald Räcke 290/387

Cuckoo Hashing

The probability that a given path-structure of size \( s \) is active is at most \[ \mu^2 n^2 s. \]

The probability that there exists an active path-structure of size \( s \) is at most \[ 2 \cdot n^s m + 1 \cdot m^s - 1 \cdot \mu^2 n^2 s \leq 2 \mu^2 n^2 \left( \frac{1}{1 + c} \right)^s \cdot \frac{1}{m^2}. \]

Plugging in \( s = \left( \frac{2t}{3} + \frac{2}{3} \right) \) gives \[ \frac{2t^2}{3} \left( \frac{1}{(2t+1)/3} \right) \leq 2 \mu^2 n^2 \left( \frac{1}{1 + c} \right)^{2t/3+1/3}. \]

Cuckoo Hashing

We choose \( \ell \geq \frac{3t}{2} + \frac{1}{2} \). Then the probability that a phase terminates unsuccessfully without running into a cycle is at most \( \frac{1}{m^2} \).

Observed that
\[ P(\text{successful} | \text{no cycle}) = P(\text{no cycle}) - P(\text{unsuccessful} | \text{no cycle}) \leq c \cdot P(\text{no cycle}) \]

So far we estimated
\[ P(\text{cycle}) = O \left( \frac{1}{m^2} \right) \]

We have
\[ P(\text{successful} | \text{no cycle}) \leq c \cdot P(\text{no cycle}) \leq O \left( \frac{1}{m^2} \right) \]

The probability that there exists an active path-structure of size \( s \) is at most \( \frac{1}{m^2} \).

Note that the existence of a path structure of size larger than \( s \) implies the existence of a path structure of size exactly \( s \).

This gives \( \ell \geq \log (\ell / m) \).

Note that the existence of a path structure of size at least \( \ell + 1 \) implies the existence of a path structure of size exactly \( \ell + 1 \).

by choosing \( \ell = \log (2m^2 / \log(1 + e)) \).
Cuckoo Hashing

The expected number of complete steps in the successful phase of an insert operation is:

\[
E \left[ \text{number of steps} \mid \text{phase successful} \right] = \sum_{t=1}^{\infty} \Pr[\text{search takes at least } t \text{ steps} \mid \text{phase successful}]
\]

We have

\[
\Pr[\text{search at least } t \text{ steps} \mid \text{successful}] = \Pr[\text{search at least } t \text{ steps} \land \text{successful}] / \Pr[\text{successful}]
\]

\[
\leq \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \land \text{no cycle}] / \Pr[\text{no cycle}]
\]

\[
\leq \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \land \text{no cycle}] / \Pr[\text{no cycle}]
\]

\[
= \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \mid \text{no cycle}].
\]

This means the expected cost for a successful phase is constant (even after accounting for the cost of the incomplete step that finishes the phase).

Cuckoo Hashing

Hence,

\[
E \left[ \text{number of steps} \mid \text{phase successful} \right] \leq \frac{1}{c} \sum_{t=1}^{\infty} \Pr[\text{search at least } t \text{ steps} \mid \text{no cycle}]
\]

\[
\leq \frac{1}{c} \sum_{t=1}^{\infty} 2\mu^2 \left( \frac{1}{1+\epsilon} \right)^{\frac{2(t-1)}{3}} = \frac{1}{c} \sum_{t=0}^{\infty} 2\mu^2 \left( \frac{1}{1+\epsilon} \right)^{\frac{2(t+1)-1}{3}}
\]

\[
= \frac{2\mu^2}{c(1+\epsilon)^{1/3}} \sum_{t=0}^{\infty} \left( \frac{1}{(1+\epsilon)^2/3} \right)^t = O(1).
\]

Formal Proof

Let \(Y_i\) denote the event that the \(i\)-th rehash does not lead to a valid configuration (assuming \(i\)-th rehash occurs) (i.e., one of the \(m+1\) insertions fails):

\[
\Pr[Y_i] \leq (m+1) \cdot O(1/m^2) \leq O(1/m) =: p.
\]

Let \(Z_i\) denote the event that the \(i\)-th rehash occurs:

\[
\Pr[Z_i] \leq \Pr[\bigwedge_{j=0}^{i-1} Y_j] \leq p^i.
\]

Let \(X_s^i, s \in \{1, \ldots, m+1\}\) denote the cost for inserting the \(s\)-th element during the \(i\)-th rehash (assuming \(i\)-th rehash occurs):

\[
E[X_s^i] = E[\text{steps} \mid \text{phase successful}] \cdot \Pr[\text{phase successful}] + \text{maxsteps} \cdot \Pr[\text{not successful}] = O(1).
\]
The expected cost for all rehashes is

\[ E \left[ \sum_i \sum_s Z_i X_{ij} \right] \]

Note that \( Z_i \) is independent of \( X_{ij}^j, j \geq i \) (however, it is not independent of \( X_{ij}^j, j < i \)). Hence,

\[
E \left[ \sum_i \sum_s Z_i X_{ij} \right] = \sum_i \sum_s E[Z_i] \cdot E[X_{ij}^j] \\
\leq \Theta(m) \cdot \sum_i p^j \\
\leq \Theta(m) \cdot \frac{p}{1 - p} \\
= \Theta(1).
\]

Cuckoo Hashing

What kind of hash-functions do we need?
Since \( \text{maxsteps} \) is \( \Theta(\log m) \) the largest size of a path-structure or cycle-structure contains just \( \Theta(\log m) \) different keys. Therefore, it is sufficient to have \((\mu, \Theta(\log m))\)-independent hash-functions.

Cuckoo Hashing

How do we make sure that \( n \geq (1 + \epsilon)m \)?

- Let \( \alpha := 1/(1 + \epsilon) \).
- Keep track of the number of elements in the table. When \( m \geq \alpha n \) we double \( n \) and do a complete re-hash (table-expand).
- Whenever \( m \) drops below \( \alpha n / 4 \) we divide \( n \) by 2 and do a rehash (table-shrink).
- Note that right after a change in table-size we have \( m = \alpha n / 2 \). In order for a table-expand to occur at least \( \alpha n / 2 \) insertions are required. Similar, for a table-shrink at least \( \alpha n / 4 \) deletions must occur.
- Therefore we can amortize the rehash cost after a change in table-size against the cost for insertions and deletions.

Cuckoo Hashing

Lemma 23

Cuckoo Hashing has an expected constant insert-time and a worst-case constant search-time.

Note that the above lemma only holds if the fill-factor (number of keys/total number of hash-table slots) is at most \( \frac{1}{2(1+\epsilon)} \).
8 Priority Queues

A Priority Queue $S$ is a dynamic set data structure that supports the following operations:

- **$S$.build($x_1, \ldots, x_n$)**: Creates a data-structure that contains just the elements $x_1, \ldots, x_n$.
- **$S$.insert($x$)**: Adds element $x$ to the data-structure.
- **$S$.minimum()** Returns an element $x \in S$ with minimum key-value $\text{key}[x]$.
- **$S$.delete-min()** Deletes the element with minimum key-value from $S$ and returns it.
- **boolean $S$.is-empty()** Returns true if the data-structure is empty and false otherwise.

Sometimes we also have
- **$S$.merge($S'$)**: $S := S \cup S'$; $S' := \emptyset$.

Reference for Cuckoo Hashing???

### Dijkstra’s Shortest Path Algorithm

**Algorithm 14 Shortest-Path**

$G = (V, E, d), s \in V$

1. **Input**: weighted graph $G = (V, E, d)$; start vertex $s$;
2. **Output**: key-field of every node contains distance from $s$;
3. $S$.build(); // build empty priority queue
4. **for all** $v \in V \setminus \{s\}$ **do**
   5. $v$.key $\leftarrow \infty$;
   6. $h_v \leftarrow S$.insert($v$);
   7. $s$.key $\leftarrow 0$; $S$.insert($s$);
8. **while** $S$.is-empty() = false **do**
   9. $v \leftarrow S$.delete-min();
10. **for all** $x \in V$ s.t. $(v, x) \in E$ **do**
    11. if $x$.key > $v$.key + $d(v, x)$ then
    12. $S$.decrease-key($h_x, v$.key + $d(v, x)$);
    13. $x$.key $\leftarrow v$.key + $d(v, x)$;
Prim’s Minimum Spanning Tree Algorithm

Algorithm 15 Prim-MST \((G = (V, E, d), s \in V)\)

1: Input: weighted graph \(G = (V, E, d)\); start vertex \(s\);
2: Output: pred-fields encode MST;
3: \(S\).build(); // build empty priority queue
4: for all \(v \in V\) \{\(s\}\) do
5: \(v\).key ← ∞;
6: \(h_v\) ← \(S\).insert(\(v\));
7: \(s\).key ← 0; \(S\).insert(\(s\));
8: while \(S\).is-empty() = false do
9: \(v\) ← \(S\).delete-min();
10: for all \(x \in V\) s.t. \(\{v, x\}\) ∈ \(E\) do
11: if \(x\).key > \(d(v, x)\) then
12: \(S\).decrease-key(h\(x\), \(d(v, x)\));
13: \(x\).key ← \(d(v, x)\);
14: \(x\).pred ← \(v\);

Analysis of Dijkstra and Prim

Both algorithms require:

- \(1\) build() operation
- \(|V|\) insert() operations
- \(|V|\) delete-min() operations
- \(|V|\) is-empty() operations
- \(|E|\) decrease-key() operations

How good a running time can we obtain?

8 Priority Queues

Using Binary Heaps, Prim and Dijkstra run in time \(\Theta((|V| + |E|) \log |V|)\).

Using Fibonacci Heaps, Prim and Dijkstra run in time \(\Theta(|V| \log |V| + |E|)\).

8 Priority Queues

<table>
<thead>
<tr>
<th>Operation</th>
<th>Binary Heap</th>
<th>BST</th>
<th>Binomial Heap</th>
<th>Fibonacci Heap</th>
</tr>
</thead>
<tbody>
<tr>
<td>build</td>
<td>(n)</td>
<td>(n\ log n)</td>
<td>(n \ log n)</td>
<td>(n)</td>
</tr>
<tr>
<td>minimum</td>
<td>(1)</td>
<td>(\log n)</td>
<td>(\log n)</td>
<td>(1)</td>
</tr>
<tr>
<td>is-empty</td>
<td>(1)</td>
<td>(\log n)</td>
<td>(\log n)</td>
<td>(1)</td>
</tr>
<tr>
<td>insert</td>
<td>(\log n)</td>
<td>(\log n)</td>
<td>(\log n)</td>
<td>(1)</td>
</tr>
<tr>
<td>delete</td>
<td>(\log n^\ast)</td>
<td>(\log n)</td>
<td>(\log n)</td>
<td>(\log n)</td>
</tr>
<tr>
<td>delete-min</td>
<td>(\log n)</td>
<td>(\log n)</td>
<td>(\log n)</td>
<td>(\log n)</td>
</tr>
<tr>
<td>decrease-key</td>
<td>(\log n)</td>
<td>(\log n)</td>
<td>(\log n)</td>
<td>(1)</td>
</tr>
<tr>
<td>merge</td>
<td>(n)</td>
<td>(n \ log n)</td>
<td>(n \ log n)</td>
<td>(1)</td>
</tr>
</tbody>
</table>

Note that most applications use build() only to create an empty heap which then costs time 1.

* Fibonacci heaps only give an amortized guarantee. ** The standard version of binary heaps is not addressable. Hence, it does not support a delete.
8.1 Binary Heaps

- Nearly complete binary tree; only the last level is not full, and this one is filled from left to right.
- **Heap property**: A node’s key is not larger than the key of one of its children.

Operations:

- **minimum**(): return the root-element. Time $O(1)$.
- **is-empty**(): check whether root-pointer is null. Time $O(1)$.

Maintain a pointer to the last element $x$.

- We can compute the predecessor of $x$ (last element when $x$ is deleted) in time $O(\log n)$.
  - go up until the last edge used was a right edge.
  - go left; go right until you reach a leaf.
  - if you hit the root on the way up, go to the rightmost element.

Maintain a pointer to the last element $x$.

- We can compute the successor of $x$ (last element when an element is inserted) in time $O(\log n)$.
  - go up until the last edge used was a left edge.
  - go right; go left until you reach a null-pointer.
  - if you hit the root on the way up, go to the leftmost element; insert a new element as a left child;
**Insert**

1. Insert element at successor of \( x \).
2. Exchange with parent until heap property is fulfilled.

Note that an exchange can either be done by moving the data or by changing pointers. The latter method leads to an addressable priority queue.

**Delete**

1. Exchange the element to be deleted with the element \( e \) pointed to by \( x \).
2. Restore the heap-property for the element \( e \).

At its new position \( e \) may either travel up or down in the tree (but not both directions).

**Binary Heaps**

**Operations:**

- \texttt{minimum}(): return the root-element. Time \( \Theta(1) \).
- \texttt{is-empty}(): check whether root-pointer is \texttt{null}. Time \( \Theta(1) \).
- \texttt{insert}(\( k \)): insert at successor of \( x \) and bubble up. Time \( \Theta(\log n) \).
- \texttt{delete}(\( h \)): swap with \( x \) and bubble up or sift-down. Time \( \Theta(\log n) \).

**Build Heap**

We can build a heap in linear time:

\[
\sum_{\ell \leq h} 2^{\ell} \cdot (h - \ell) = \sum_i i2^{h-i} = \Theta(2^h) = \Theta(n)
\]
Binary Heaps

Operations:
- **minimum()**: Return the root-element. Time $O(1)$.
- **is-empty()**: Check whether root-pointer is null. Time $O(1)$.
- **insert(k)**: Insert at $x$ and bubble up. Time $O(\log n)$.
- **delete(h)**: Swap with $x$ and bubble up or sift-down. Time $O(\log n)$.
- **build(x_1, \ldots, x_n)**: Insert elements arbitrarily; then do sift-down operations starting with the lowest layer in the tree. Time $O(n)$.

8.1 Binary Heaps

The standard implementation of binary heaps is via arrays. Let $A[0, \ldots, n-1]$ be an array
- The parent of $i$-th element is at position $\lfloor \frac{i-1}{2} \rfloor$.
- The left child of $i$-th element is at position $2i + 1$.
- The right child of $i$-th element is at position $2i + 2$.
Finding the successor of $x$ is much easier than in the description on the previous slide. Simply increase or decrease $x$.
The resulting binary heap is not addressable. The elements don’t maintain their positions and therefore there are no stable handles.

8.2 Binomial Heaps

<table>
<thead>
<tr>
<th>Operation</th>
<th>Binary Heap</th>
<th>BST</th>
<th>Binomial Heap</th>
<th>Fibonacci Heap</th>
</tr>
</thead>
<tbody>
<tr>
<td>build</td>
<td>$n$</td>
<td>$n \log n$</td>
<td>$n \log n$</td>
<td>$n$</td>
</tr>
<tr>
<td>minimum</td>
<td>1</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>1</td>
</tr>
<tr>
<td>is-empty</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>insert</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>1</td>
</tr>
<tr>
<td>delete</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
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<td>delete-min</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
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<tr>
<td>decrease-key</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>$\log n$</td>
<td>1</td>
</tr>
<tr>
<td>merge</td>
<td>$n$</td>
<td>$n \log n$</td>
<td>$\log n$</td>
<td>1</td>
</tr>
</tbody>
</table>

8.2 Binomial Heaps

8.2 Binomial Heaps

8.2 Binomial Heaps

8.2 Binomial Heaps
Binomial Trees

Properties of Binomial Trees

- \( B_k \) has \( 2^k \) nodes.
- \( B_k \) has height \( k \).
- The root of \( B_k \) has degree \( k \).
- \( B_k \) has \( \binom{k}{\ell} \) nodes on level \( \ell \).
- Deleting the root of \( B_k \) gives trees \( B_0, B_1, \ldots, B_{k-1} \).

Deleting the root of \( B_5 \) leaves sub-trees \( B_4, B_3, B_2, B_1, \) and \( B_0 \).

Deleting the leaf furthest from the root (in \( B_3 \)) leaves a path that connects the roots of sub-trees \( B_4, B_3, B_2, B_1, \) and \( B_0 \).

The number of nodes on level \( \ell \) in tree \( B_k \) is therefore

\[
\binom{k-1}{\ell-1} + \binom{k-1}{\ell} = \binom{k}{\ell}.
\]
The binomial tree $B_k$ is a sub-graph of the hypercube $H_k$.

The parent of a node with label $b_n, \ldots, b_1, b_0$ is obtained by setting the least significant 1-bit to 0.

The $\ell$-th level contains nodes that have $\ell$ 1’s in their label.

- Given a pointer to a node $x$ we can splice out the sub-tree rooted at $x$ in constant time.
- We can add a child-tree $T$ to a node $x$ in constant time if we are given a pointer to $x$ and a pointer to the root of $T$.

In a binomial heap the keys are arranged in a collection of binomial trees.

Every tree fulfills the heap-property

There is at most one tree for every dimension/order. For example the above heap contains trees $B_0$, $B_1$, and $B_4$. 

Binomial Heap: Merge

Given the number $n$ of keys to be stored in a binomial heap we can deduce the binomial trees that will be contained in the collection.

Let $B_{k_1}, B_{k_2}, B_{k_3}, k_i < k_{i+1}$ denote the binomial trees in the collection and recall that every tree may be contained at most once.

Then $n = \sum_i 2^{k_i}$ must hold. But since the $k_i$ are all distinct this means that the $k_i$ define the non-zero bit-positions in the binary representation of $n$.

Binomial Heap: Merge

The merge-operation is instrumental for binomial heaps.

A merge is easy if we have two heaps with different binomial trees. We can simply merge the tree-lists.

Otherwise, we cannot do this because the merged heap is not allowed to contain two trees of the same order.

Merging two trees of the same size: Add the tree with larger root-value as a child to the other tree.

For more trees the technique is analogous to binary addition.
8.2 Binomial Heaps

\[ S_1. \text{merge}(S_2): \]
- Analogous to binary addition.
- Time is proportional to the number of trees in both heaps.
- Time: \( O(\log n) \).

8.2 Binomial Heaps

All other operations can be reduced to \text{merge}().

\[ S. \text{insert}(x): \]
- Create a new heap \( S' \) that contains just the element \( x \).
- Execute \( S.\text{merge}(S') \).
- Time: \( O(\log n) \).

8.2 Binomial Heaps

\[ S. \text{minimum}(): \]
- Find the minimum key-value among all roots.
- Time: \( O(\log n) \).

8.2 Binomial Heaps

\[ S. \text{delete-min}(): \]
- Find the minimum key-value among all roots.
- Remove the corresponding tree \( T_{\text{min}} \) from the heap.
- Create a new heap \( S' \) that contains the trees obtained from \( T_{\text{min}} \) after deleting the root (note that these are just \( O(\log n) \) trees).
- Compute \( S.\text{merge}(S') \).
- Time: \( O(\log n) \).
**8.2 Binomial Heaps**

*S.* decrease-key(handle *h*):

- Decrease the key of the element pointed to by *h*.
- Bubble the element up in the tree until the heap property is fulfilled.
- Time: $O(\log n)$ since the trees have height $O(\log n)$.

*S.* delete(handle *h*):

- Execute *S.* decrease-key(*h*, $-\infty$).
- Execute *S.* delete-min().
- Time: $O(\log n)$.

**8.3 Fibonacci Heaps**

Collection of trees that fulfill the heap property.

Structure is much more relaxed than binomial heaps.

Additional implementation details:

- Every node *x* stores its degree in a field *x*.degree. Note that this can be updated in constant time when adding a child to *x*.
- Every node stores a boolean value *x*.marked that specifies whether *x* is marked or not.
8.3 Fibonacci Heaps

The potential function:
- $t(S)$ denotes the number of trees in the heap.
- $m(S)$ denotes the number of marked nodes.
- We use the potential function $\Phi(S) = t(S) + 2m(S)$.

The potential is $\Phi(S) = 5 + 2 \cdot 3 = 11$.

8.3 Fibonacci Heaps

We assume that one unit of potential can pay for a constant amount of work, where the constant is chosen “big enough” (to take care of the constants that occur).

To make this more explicit we use $c$ to denote the amount of work that a unit of potential can pay for.

8.3 Fibonacci Heaps

$S$. minimum

- Access through the min-pointer.
- Actual cost $O(1)$.
- No change in potential.
- Amortized cost $O(1)$.

8.3 Fibonacci Heaps

$S$. merge($S'$)

- Merge the root lists.
- Adjust the min-pointer

Running time:
- Actual cost $O(1)$.
- No change in potential.
- Hence, amortized cost is $O(1)$. 
8.3 Fibonacci Heaps

S. insert \( x \)

- Create a new tree containing \( x \).
- Insert \( x \) into the root-list.
- Update min-pointer, if necessary.

Running time:

- Actual cost \( \mathcal{O}(1) \).
- Change in potential is +1.
- Amortized cost is \( c + \mathcal{O}(1) = \mathcal{O}(1) \).

8.3 Fibonacci Heaps

\( D(\min) \) is the number of children of the node that stores the minimum.

S. delete-min \( x \)

- Delete minimum; add child-trees to heap; time: \( D(\min) \cdot \mathcal{O}(1) \).
- Update min-pointer; time: \( (t + D(\min)) \cdot \mathcal{O}(1) \).

8.3 Fibonacci Heaps

\( D(\min) \) is the number of children of the node that stores the minimum.

S. delete-min \( x \)

- Delete minimum; add child-trees to heap; time: \( D(\min) \cdot \mathcal{O}(1) \).
- Update min-pointer; time: \( (t + D(\min)) \cdot \mathcal{O}(1) \).

8.3 Fibonacci Heaps

**Consolidate:**

- Consolidate root-list so that no roots have the same degree.
  
  Time \( t \cdot \mathcal{O}(1) \) (see next slide).
8.3 Fibonacci Heaps

Consolidate:

Consolidate:

Consolidate:

Consolidate:
8.3 Fibonacci Heaps

Consolidate:

current

min → 7

8.3 Fibonacci Heaps

Consolidate:

current

min → 7

8.3 Fibonacci Heaps

Consolidate:

current

min → 7

8.3 Fibonacci Heaps

Consolidate:

current

min → 7
If the input trees of the consolidation procedure are binomial trees (for example only singleton vertices) then the output will be a set of distinct binomial trees, and, hence, the Fibonacci heap will be (more or less) a Binomial heap right after the consolidation.

If we do not have delete or decrease-key operations then $D_n \leq \log n$.

---

**Fibonacci Heaps: decrease-key**

**Case 1: decrease-key does not violate heap-property**
- Just decrease the key-value of element referenced by $h$.
- Nothing else to do.

**Case 2: heap-property is violated, but parent is not marked**
- Decrease key-value of element $x$ reference by $h$.
- If the heap-property is violated, cut the parent edge of $x$, and make $x$ into a root.
- Adjust min-pointers, if necessary.
- Mark the (previous) parent of $x$ (unless it’s a root).
Fibonacci Heaps: decrease-key(handle $h$, $v$)

**Case 2: heap-property is violated, but parent is not marked**
- Decrease key-value of element $x$ reference by $h$.
- If the heap-property is violated, cut the parent edge of $x$, and make $x$ into a root.
- Adjust min-pointers, if necessary.
- Mark the (previous) parent of $x$ (unless it’s a root).

**Marking a node can be viewed as a first step towards becoming a root. The first time $x$ loses a child it is marked; the second time it loses a child it is made into a root.**

**Case 3: heap-property is violated, and parent is marked**
- Decrease key-value of element $x$ reference by $h$.
- Cut the parent edge of $x$, and make $x$ into a root.
- Adjust min-pointers, if necessary.
- Continue cutting the parent until you arrive at an unmarked node.

- If $p$ is unmarked and not a root mark it;
Fibonacci Heaps: \texttt{decrease-key}(h, v)

**Actual cost:**
- Constant cost for decreasing the value.
- Constant cost for each of \(\ell\) cuts.
- Hence, cost is at most \(c_2 \cdot (\ell + 1)\), for some constant \(c_2\).

**Amortized cost:**
- \(t' = t + \ell\), as every cut creates one new root.
- \(m' \leq m - (\ell - 1) + 1 = m - \ell + 2\), since all but the first cut unmarks a node; the last cut may mark a node.
- \(\Delta \Phi \leq \ell + 2(-\ell + 2) = 4 - \ell\)
- Amortized cost is at most \(c_2(\ell + 1) + c(4 - \ell) \leq (c_2 - c)\ell + 4c + c_2 = O(1)\),
  \[\text{if } c \geq c_2.\]

Delete node

Let \(x\) be a node with degree \(k\) and let \(y_1, \ldots, y_k\) denote the children of \(x\) in the order that they were linked to \(x\). Then
\[
\text{degree}(y_i) \geq \begin{cases} 
0 & \text{if } i = 1 \\
\ell - 2 & \text{if } i > 1 
\end{cases}
\]

The marking process is very important for the proof of this lemma. It ensures that a node can have lost at most one child since the last time it became a non-root node.

When losing a first child the node gets marked; when losing the second child it is cut from the parent and made into a root.
Let \( s_k \) be the minimum possible size of a sub-tree rooted at a node of degree \( k \) that can occur in a Fibonacci heap.

- \( s_k \) monotonically increases with \( k \)
- \( s_0 = 1 \) and \( s_1 = 2 \).

Let \( x \) be a degree \( k \) node of size \( s_k \) and let \( y_1, \ldots, y_k \) be its children.

\[
s_k = 2 + \sum_{i=2}^{k} \text{size}(y_i) \\
\geq 2 + \sum_{i=2}^{k} s_{i-2} \\
= 2 + \sum_{i=0}^{k-2} s_i
\]

### Definition 25
Consider the following non-standard Fibonacci type sequence:

\[
F_k = \begin{cases} 
1 & \text{if } k = 0 \\
2 & \text{if } k = 1 \\
F_{k-1} + F_{k-2} & \text{if } k \geq 2
\end{cases}
\]

#### Facts:
1. \( F_k \geq \phi^k \).
2. For \( k \geq 2 \): \( F_k = 2 + \sum_{i=0}^{k-2} F_i \).

The above facts can be easily proved by induction. From this it follows that \( s_k \geq F_k \geq \phi^k \), which gives that the maximum degree in a Fibonacci heap is logarithmic.
9 Union Find

Union Find Data Structure $\mathcal{P}$: Maintains a partition of disjoint sets over elements.

- $\mathcal{P}.\text{makeset}(x)$: Given an element $x$, adds $x$ to the data-structure and creates a singleton set that contains only this element. Returns a locator/handle for $x$ in the data-structure.
- $\mathcal{P}.\text{find}(x)$: Given a handle for an element $x$; find the set that contains $x$. Returns a representative/identifier for this set.
- $\mathcal{P}.\text{union}(x,y)$: Given two elements $x$, and $y$ that are currently in sets $S_x$ and $S_y$, respectively, the function replaces $S_x$ and $S_y$ by $S_x \cup S_y$ and returns an identifier for the new set.

9 Union Find

Applications:
- Keep track of the connected components of a dynamic graph that changes due to insertion of nodes and edges.
- Kruskals Minimum Spanning Tree Algorithm

Algorithm 16 Kruskal-MST($G = (V, E), w$)

1: $A \leftarrow \emptyset$;
2: for all $v \in V$ do
3: $v.\text{set} \leftarrow \mathcal{P}.\text{makeset}(v.\text{label})$
4: sort edges in non-decreasing order of weight $w$
5: for all $(u, v) \in E$ in non-decreasing order do
6: if $\mathcal{P}.\text{find}(u.\text{set}) \neq \mathcal{P}.\text{find}(v.\text{set})$ then
7: $A \leftarrow A \cup \{(u, v)\}$
8: $\mathcal{P}.\text{union}(u.\text{set}, v.\text{set})$

List Implementation

- The elements of a set are stored in a list; each node has a backward pointer to the head.
- The head of the list contains the identifier for the set and a field that stores the size of the set.

- $\text{makeset}(x)$ can be performed in constant time.
- $\text{find}(x)$ can be performed in constant time.
List Implementation

\textbf{union}(x, y)

\begin{itemize}
  \item Determine sets \(S_x\) and \(S_y\).
  \item Traverse the smaller list (say \(S_y\)), and change all backward pointers to the head of list \(S_x\).
  \item Insert list \(S_y\) at the head of \(S_x\).
  \item Adjust the size-field of list \(S_x\).
  \item Time: \(\min\{|S_x|, |S_y|\}\).
\end{itemize}

\textbf{Running times:}

\begin{itemize}
  \item \textbf{find}(x): constant
  \item \textbf{makeset}(x): constant
  \item \textbf{union}(x, y): \(O(n)\), where \(n\) denotes the number of elements contained in the set system.
\end{itemize}
Lemma 26
The list implementation for the ADT union find fulfills the following amortized time bounds:

- \( \text{find}(x) \): \( O(1) \).
- \( \text{makeSet}(x) \): \( O(\log n) \).
- \( \text{union}(x, y) \): \( O(1) \).

The Accounting Method for Amortized Time Bounds

- There is a bank account for every element in the data structure.
- Initially the balance on all accounts is zero.
- Whenever for an operation the amortized time bound exceeds the actual cost, the difference is credited to some bank accounts of elements involved.
- Whenever for an operation the actual cost exceeds the amortized time bound, the difference is charged to bank accounts of some of the elements involved.
- If we can find a charging scheme that guarantees that balances always stay positive the amortized time bounds are proven.

List Implementation

- For an operation whose actual cost exceeds the amortized cost we charge the excess to the elements involved.
- In total we will charge at most \( O(\log n) \) to an element (regardless of the request sequence).
- For each element a makeset operation occurs as the first operation involving this element.
- We inflate the amortized cost of the makeset-operation to \( \Theta(\log n) \), i.e., at this point we fill the bank account of the element to \( \Theta(\log n) \).
- Later operations charge the account but the balance never drops below zero.

makeset\((x)\): The actual cost is \( O(1) \). Due to the cost inflation the amortized cost is \( O(\log n) \).

\( \text{find}(x) \): For this operation we define the amortized cost and the actual cost to be the same. Hence, this operation does not change any accounts. Cost: \( O(1) \).

\( \text{union}(x, y) \):

- If \( S_x = S_y \) the cost is constant; no bank accounts change.
- Otw. the actual cost is \( O(\min\{|S_x|, |S_y|\}) \).
- Assume wlog. that \( S_x \) is the smaller set; let \( c \) denote the hidden constant, i.e., the actual cost is at most \( c \cdot |S_x| \).
- Charge \( c \) to every element in set \( S_x \).
List Implementation

Lemma 27
An element is charged at most \(\lceil \log_2 n \rceil\) times, where \(n\) is the total number of elements in the set system.

Proof.
Whenever an element \(x\) is charged the number of elements in \(x\)'s set doubles. This can happen at most \(\lceil \log n \rceil\) times. \(\square\)

Implementation via Trees

- Maintain nodes of a set in a tree.
- The root of the tree is the label of the set.
- Only pointer to parent exists; we cannot list all elements of a given set.
- Example:

\[
\begin{array}{c}
\text{Set system} \{2, 5, 10, 12\}, \{3, 6, 7, 8, 9, 14, 17\}, \{16, 19, 23\}.
\end{array}
\]

Implementation via Trees

\textbf{makeset}(x)

- Create a singleton tree. Return pointer to the root.
- Time: \(O(1)\).

\textbf{find}(x)

- Start at element \(x\) in the tree. Go upwards until you reach the root.
- Time: \(O(\text{level}(x))\), where \(\text{level}(x)\) is the distance of element \(x\) to the root in its tree. \textbf{Not constant}.}

\textbf{union}(x, y)

- Perform \(a \leftarrow \text{find}(x)\); \(b \leftarrow \text{find}(y)\). Then: \(\text{link}(a, b)\).
- \(\text{link}(a, b)\) attaches the smaller tree as the child of the larger.
- In addition it updates the size-field of the new root.

\[
\begin{array}{c}
\text{Time: constant for } \text{link}(a, b) \text{ plus two find-operations.}
\end{array}
\]
Implementation via Trees

Lemma 28
The running time (non-amortized!!!) for find(x) is \( O(\log n) \).

Proof.
- When we attach a tree with root \( c \) to become a child of a tree with root \( p \), then \( \text{size}(p) \geq 2 \text{size}(c) \), where size denotes the value of the size-field right after the operation.
- After that the value of size(c) stays fixed, while the value of size(p) may still increase.
- Hence, at any point in time a tree fulfills \( \text{size}(p) \geq 2 \text{size}(c) \), for any pair of nodes \( (p, c) \), where \( p \) is a parent of \( c \).

Path Compression

find(x):
- Go upward until you find the root.
- Re-attach all visited nodes as children of the root.
- Speeds up successive find-operations.

Path Compression

Asymptotically the cost for a find-operation does not increase due to the path compression heuristic.

However, for a worst-case analysis there is no improvement on the running time. It can still happen that a find-operation takes time \( O(\log n) \).
Amortized Analysis

Definitions:

- \( \text{size}(v) \) = the number of nodes that were in the sub-tree rooted at \( v \) when \( v \) became the child of another node (or the number of nodes if \( v \) is the root).
  
  Note that this is the same as the size of \( v \)'s subtree in the case that there are no find-operations.

- \( \text{rank}(v) = \lfloor \log(\text{size}(v)) \rfloor \).

  \( \Rightarrow \) \( \text{size}(v) \geq 2^{\text{rank}(v)} \).

Lemma 29

The rank of a parent must be strictly larger than the rank of a child.

Lemma 30

There are at most \( n/2^s \) nodes of rank \( s \).

Proof.

- Let's say a node \( v \) sees node \( x \) if \( v \) is in \( x \)'s sub-tree at the time that \( x \) becomes a child.

- A node \( v \) sees at most one node of rank \( s \) during the running time of the algorithm.

- This holds because the rank-sequence of the roots of the different trees that contain \( v \) during the running time of the algorithm is a strictly increasing sequence.

- Hence, every node sees at most one rank \( s \) node, but every rank \( s \) node is seen by at least \( 2^s \) different nodes.

Amortized Analysis

We define

\[
tow(i) := \begin{cases} 
1 & \text{if } i = 0 \\
2^{tow(i-1)} & \text{otherwise} \\
2^{2^{i+2}}i \text{ times} 
\end{cases}
\]

and

\[
\log^*(n) := \min\{i \mid tow(i) \geq n\} .
\]

Theorem 31

Union find with path compression fulfills the following amortized running times:

- \( \text{makeset}(x) : \mathcal{O}(\log^*(n)) \)

- \( \text{find}(x) : \mathcal{O}(\log^*(n)) \)

- \( \text{union}(x,x') : \mathcal{O}(\log^*(n)) \)

In the following we assume \( n \geq 2 \).

- rank-group:

  - A node with rank \( \text{rank}(v) \) is in rank group \( \log^*(\text{rank}(v)) \).
  
  - The rank-group \( g = 0 \) contains only nodes with rank 0 or rank 1.
  
  - A rank group \( g \geq 1 \) contains ranks \( tow(g-1) + 1, \ldots, tow(g) \).
  
  - The maximum non-empty rank group is \( \log^*(\lfloor \log n \rfloor) \leq \log^*(n) - 1 \) (which holds for \( n \geq 2 \)).

  - Hence, the total number of rank-groups is at most \( \log^* n \).
Amortized Analysis

Accounting Scheme:
▶ create an account for every find-operation
▶ create an account for every node \( v \)

The cost for a find-operation is equal to the length of the path traversed. We charge the cost for going from \( v \) to \( \text{parent}[v] \) as follows:
▶ If \( \text{parent}[v] \) is the root we charge the cost to the find-account.
▶ If the group-number of \( \text{rank}(v) \) is the same as that of \( \text{rank}(\text{parent}[v]) \) (before starting path compression) we charge the cost to the node-account of \( v \).
▶ Otherwise we charge the cost to the find-account.

Amortized Analysis

Observations:
▶ A find-account is charged at most \( \log^*(n) \) times (once for the root and at most \( \log^*(n) - 1 \) times when increasing the rank-group).
▶ After a node \( v \) is charged its parent-edge is re-assigned. The rank of the parent strictly increases.
▶ After some charges to \( v \) the parent will be in a larger rank-group. \( \Rightarrow \) \( v \) will never be charged again.
▶ The total charge made to a node in rank-group \( g \) is at most \( \text{tow}(g) - \text{tow}(g-1) - 1 \leq \text{tow}(g) \).

Amortized Analysis

What is the total charge made to nodes?
▶ The total charge is at most
\[
\sum_{g} n(g) \cdot \text{tow}(g) ,
\]
where \( n(g) \) is the number of nodes in group \( g \).

Amortized Analysis

For \( g \geq 1 \) we have
\[
n(g) \leq \sum_{s = \text{tow}(g-1) + 1}^{\text{tow}(g)} \frac{n}{2^s} \leq \sum_{s = \text{tow}(g-1) + 1}^{\infty} \frac{n}{2^s} = \frac{n}{2^{\text{tow}(g-1) + 1}} \cdot 2 = \frac{n}{2^{\text{tow}(g-1)}} = \frac{n}{\text{tow}(g)} .
\]

Hence,
\[
\sum_{g} n(g) \text{tow}(g) \leq n(0) \text{tow}(0) + \sum_{g=1} n(g) \text{tow}(g) \leq n \log^*(n)
\]
Amortized Analysis

Without loss of generality we can assume that all makeset-operations occur at the start.

This means if we inflate the cost of makeset to $\log^* n$ and add this to the node account of $v$ then the balances of all node accounts will sum up to a positive value (this is sufficient to obtain an amortized bound).

The analysis is not tight. In fact it has been shown that the amortized time for the union-find data structure with path compression is $O(\alpha(m,n))$, where $\alpha(m,n)$ is the inverse Ackermann function which grows a lot lot slower than $\log^* n$. (Here, we consider the average running time of $m$ operations on at most $n$ elements).

There is also a lower bound of $\Omega(\alpha(m,n))$.

Amortized Analysis

\[
A(x,y) = \begin{cases} 
   y + 1 & \text{if } x = 0 \\
   A(x - 1,1) & \text{if } y = 0 \\
   A(x - 1,A(x,y - 1)) & \text{otherwise}
\end{cases}
\]

\[
\alpha(m,n) = \min\{i \geq 1 : A(i,\lfloor m/n \rfloor) \geq \log n\}
\]

- $A(0,y) = y + 1$
- $A(1,y) = y + 2$
- $A(2,y) = 2y + 3$
- $A(3,y) = 2^{y+3} - 3$
- $A(4,y) = \left(2^{2^y} - 3\right)^{\text{y+3 times}}$

Union Find

Bibliography


Union find data structures are discussed in Chapter 21 of [CLRS90a] and [CLRS90b] and in Chapter 22 of [CLRS90c]. The analysis of union by rank with path compression can be found in [CLRS90a] but neither in [CLRS90b] in nor in [CLRS90c]. The latter books contains a more involved analysis that gives a better bound than $O(\log^* n)$.

A description of the $O(\log^* n)$ bound can also be found in Chapter 4.8 of [AHU74].