7 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 $\text{key}[e] = k$ 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 \( \text{key}[v] \) 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:
7.1 Binary Search Trees

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 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)
### Binary Search Trees: Searching

**Algorithm 1** \( \text{TreeSearch}(x, k) \)

1. **if** \( x = \text{null} \) or \( k = \text{key}[x] \) **return** \( x \)
2. **if** \( k < \text{key}[x] \) **return** \( \text{TreeSearch}(\text{left}[x], k) \)
3. **else** **return** \( \text{TreeSearch}(\text{right}[x], k) \)
Binary Search Trees: Searching

TreeSearch(root, 17)

Algorithm 1 TreeSearch(x, k)
1: if x = null or k = key[x] return x
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1: if x = null or k = key[x] return x
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3: else return TreeSearch(right[x], k)
Binary Search Trees: Searching

TreeSearch(root, 17)

![Binary Search Tree Diagram]

**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 1 TreeSearch($x, k$)

1. $\textbf{if } x = \text{null or } k = \text{key}[x] \textbf{ return } x$
2. $\textbf{if } k < \text{key}[x] \textbf{ return } \text{TreeSearch}(\text{left}[x], k)$
3. $\textbf{else return } \text{TreeSearch}(\text{right}[x], k)$
Binary Search Trees: Searching

Algorithm 1 \text{TreeSearch}(x, k)

1: \textbf{if} \ x = \text{null} \ \textbf{or} \ k = \text{key}[x] \ \textbf{return} \ x
2: \textbf{if} \ k < \text{key}[x] \ \textbf{return} \ \text{TreeSearch}(\text{left}[x], k)
3: \textbf{else return} \ \text{TreeSearch}(\text{right}[x], k)
Binary Search Trees: Searching

TreeSearch(root, 8)

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)
Binary Search Trees: Searching

TreeSearch(root, 8)

```
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 1 TreeSearch\((x, k)\)

1: if \(x = \text{null}\) or \(k = \text{key}[x]\) return \(x\)
2: if \(k < \text{key}[x]\) return TreeSearch(left\([x]\), \(k\))
3: else return TreeSearch(right\([x]\), \(k\))
Binary Search Trees: Searching

TreeSearch(root, 8)

Algorithm 1 TreeSearch(x, k)
1: if x = null or k = key[x] return x
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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)
Binary Search Trees: Minimum

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

1: if $x = \text{null}$ or left[$x$] = null return $x$
2: return TreeMin(left[$x$])
Algorithm 2 TreeMin(x)

1: if x = null or left[x] = null return x
2: return TreeMin(left[x])
Algorithm 2 $\text{TreeMin}(x)$

1. if $x = \text{null}$ or $\text{left}[x] = \text{null}$ return $x$
2. return $\text{TreeMin}(\text{left}[x])$
Algorithm 2 TreeMin(x)
1: if x = null or left[x] = null return x
2: return TreeMin(left[x])
Algorithm 2 TreeMin(x)
1: if x = null or left[x] = null return x
2: return TreeMin(left[x])
Algorithm 3 \( \text{TreeSucc}(x) \)

1. \( \textbf{if} \ \text{right}[x] \neq \text{null} \ \textbf{return} \ \text{TreeMin} (\text{right}[x]) \)
2. \( y \leftarrow \text{parent}[x] \)
3. \( \textbf{while} \ y \neq \text{null} \ \textbf{and} \ x = \text{right}[y] \ \textbf{do} \)
4. \( x \leftarrow y; y \leftarrow \text{parent}[x] \)
5. \( \textbf{return} \ y; \)
Algorithm 3 TreeSucc($x$)

1. if right[$x$] ≠ null return TreeMin(right[$x$])
2. $y \leftarrow$ parent[$x$]
3. while $y$ ≠ null and $x$ = right[$y$] do
   4. $x \leftarrow y$; $y \leftarrow$ parent[$x$]
4. return $y$;
Algorithm 3 TreeSucc(\(x\))

1: if right[\(x\)] ≠ null return TreeMin(right[\(x\)])
2: \(y \leftarrow \text{parent}[x]\)
3: while \(y \neq \text{null} \text{ and } x = \text{right}[y]\) do
4: \(x \leftarrow y; y \leftarrow \text{parent}[x]\)
5: return \(y\);
Binary Search Trees: Successor

Algorithm 3 $\text{TreeSucc}(x)$

1. if right[$x$] ≠ null return $\text{TreeMin}$ (right[$x$])
2. $y ← \text{parent}[x]$
3. while $y$ ≠ null and $x = \text{right}[y]$ do
   4. $x ← y$; $y ← \text{parent}[x]$
5. return $y$
Algorithm 3 TreeSucc(x)

1: if right[x] ≠ null return TreeMin(right[x])
2: \( y \leftarrow \text{parent}[x] \)
3: while \( y \neq \text{null} \) and \( x = \text{right}[y] \) do
4: \( x \leftarrow y; y \leftarrow \text{parent}[x] \)
5: return \( y \);
Algorithm 3 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;
Algorithm 3  TreeSucc($x$)

1: if $\text{right}[x] \neq \text{null}$ return $\text{TreeMin}($right$[x])$
2: $y \leftarrow \text{parent}[x]$
3: while $y \neq \text{null}$ and $x = \text{right}[y]$ do
4: $x \leftarrow y$; $y \leftarrow \text{parent}[x]$
5: return $y$;
Binary Search Trees: Insert

Algorithm 4 TreeInsert(x, z)
1: if x = null then
2:   root[T] ← z; parent[z] ← null;
3:   return;
4: if key[x] > key[z] then
5:   if left[x] = null then
6:     left[x] ← z; parent[z] ← x;
7:   else TreeInsert(left[x], z);
8: else
9:   if right[x] = null then
10:    right[x] ← z; parent[z] ← x;
11:   else TreeInsert(right[x], z);
Binary Search Trees: Insert

Insert element **not** in the tree.

**Algorithm 4** **TreeInsert**(x, z)

1: if x = null then
2: root[T] ← z; parent[z] ← null;
3: return;
4: if key[x] > key[z] then
5: if left[x] = null then
6: left[x] ← z; parent[z] ← x;
7: else TreeInsert(left[x], z);
8: else
9: if right[x] = null then
10: right[x] ← z; parent[z] ← x;
11: else TreeInsert(right[x], z);
Binary Search Trees: Insert

Insert element **not** in the tree.

Algorithm 4: TreeNode

```
if x = null then
  root[T] ← z; parent[z] ← null;
  return;
if key[x] > key[z] then
  if left[x] = null then
    left[x] ← z; parent[z] ← x;
  else TreeNode(left[x], z);
else
  if right[x] = null then
    right[x] ← z; parent[z] ← x;
  else TreeNode(right[x], z);
```

Search for $z$. At some point the search stops at a null-pointer. This is the place to insert $z$. 
Binary Search Trees: Insert

Insert element not in the tree.

**TreeInsert**(root, 20)

Search for \( z \). At some point the search stops at a null-pointer. This is the place to insert \( z \).

**Algorithm 4** TreeInsert\((x, z)\)

1: if \( x = \text{null} \) then
2: \( \text{root}[T] \leftarrow z; \text{parent}[z] \leftarrow \text{null}; \)
3: return;
4: if key\( [x] \) > key\( [z] \) then
5: if left\( [x] \) = null then
6: \( \text{left}[x] \leftarrow z; \text{parent}[z] \leftarrow x; \)
7: else TreeInsert(left\( [x], z \));
8: else
9: if right\( [x] \) = null then
10: \( \text{right}[x] \leftarrow z; \text{parent}[z] \leftarrow x; \)
11: else TreeInsert(right\( [x], z \));
Binary Search Trees: Insert

Insert element **not** in the tree.

**TreeInsert**(root, 20)

Search for $z$. At some point the search stops at a null-pointer. This is the place to insert $z$.

---

**Algorithm 4 TreeInsert**(x, z)

1: if $x = \text{null}$ then  
2: $\text{root}[T] \leftarrow z$; $\text{parent}[z] \leftarrow \text{null}$;  
3: return;  
4: if $\text{key}[x] > \text{key}[z]$ then  
5: if $\text{left}[x] = \text{null}$ then  
6: $\text{left}[x] \leftarrow z$; $\text{parent}[z] \leftarrow x$;  
7: else TreeInsert(left[x], z);  
8: else  
9: if $\text{right}[x] = \text{null}$ then  
10: $\text{right}[x] \leftarrow z$; $\text{parent}[z] \leftarrow x$;  
11: else TreeInsert(right[x], z);
Binary Search Trees: Insert

Insert element **not** in the tree.

TreelInsert(root, 20)

Search for $z$. At some point the search stops at a null-pointer. This is the place to insert $z$.

**Algorithm 4 TreelInsert($x$, $z$)**

1: if $x$ = null then
2: root[$T$] ← $z$; parent[$z$] ← null;
3: return;
4: if key[$x$] > key[$z$] then
5: if left[$x$] = null then
6: left[$x$] ← $z$; parent[$z$] ← $x$;
7: else TreelInsert(left[$x$], $z$);
8: else
9: if right[$x$] = null then
10: right[$x$] ← $z$; parent[$z$] ← $x$;
11: else TreelInsert(right[$x$], $z$);
Binary Search Trees: Insert

Insert element **not** in the tree.

**TreeInsert**(root, 20)

Search for \( z \). At some point the search stops at a null-pointer. This is the place to insert \( z \).

**Algorithm 4 TreeInsert**(\( x, z \))

1: if \( x = \) null then
2: \( \text{root}[T] \leftarrow z; \text{parent}[z] \leftarrow \) null;
3: return;
4: if key[\( x \)] > key[\( z \)] then
  5: if left[\( x \)] = null then
    6: left[\( x \)] \leftarrow z; parent[\( z \)] \leftarrow \) \( x \);
  7: else TreeInsert(left[\( x \)], \( z \));
8: else
  9: if right[\( x \)] = null then
    10: right[\( x \)] \leftarrow z; parent[\( z \)] \leftarrow \) \( x \);
  11: else TreeInsert(right[\( x \)], \( z \));
Binary Search Trees: Insert

Insert element **not** in the tree.

**TreeInsert**\((\text{root}, 20)\)

Search for \(z\). At some point the search stops at a null-pointer. This is the place to insert \(z\).

**Algorithm 4** \(\text{TreeInsert}(x, z)\)

1. **if** \(x = \text{null} \) **then**
2. \(\text{root}[T] \leftarrow z; \text{parent}[z] \leftarrow \text{null};\)
3. **return**;
4. **if** \(\text{key}[x] > \text{key}[z] \) **then**
5. **if** \(\text{left}[x] = \text{null} \) **then**
6. \(\text{left}[x] \leftarrow z; \text{parent}[z] \leftarrow x;\)
7. **else** \(\text{TreeInsert}(\text{left}[x], z);\)
8. **else**
9. **if** \(\text{right}[x] = \text{null} \) **then**
10. \(\text{right}[x] \leftarrow z; \text{parent}[z] \leftarrow x;\)
11. **else** \(\text{TreeInsert}(\text{right}[x], z);\)
Binary Search Trees: Insert

Insert element **not** in the tree.

**TreelInsert(root, 20)**

Search for \( z \). At some point the search stops at a null-pointer. This is the place to insert \( z \).

**Algorithm 4 TreelInsert\((x, z)\)**

1. if \( x = \text{null} \) then
2. \hspace{1em} \text{root}[T] \leftarrow z; \text{parent}[z] \leftarrow \text{null};
3. \hspace{1em} \text{return};
4. if \( \text{key}[x] > \text{key}[z] \) then
5. \hspace{1em} if \( \text{left}[x] = \text{null} \) then
6. \hspace{2em} \text{left}[x] \leftarrow z; \text{parent}[z] \leftarrow x;
7. \hspace{1em} else TreelInsert(left[x], z);
8. else
9. \hspace{1em} if \( \text{right}[x] = \text{null} \) then
10. \hspace{2em} \text{right}[x] \leftarrow z; \text{parent}[z] \leftarrow x;
11. else TreelInsert(right[x], z);
Binary Search Trees: Delete
Binary Search Trees: Delete

Case 1:
Element does not have any children
  ▶ Simply go to the parent and set the corresponding pointer to null.
Case 1:
Element does not have any children
   ▶ Simply go to the parent and set the corresponding pointer to **null**.
Case 1:
Element does not have any children

- Simply go to the parent and set the corresponding pointer to null.
**Binary Search Trees: Delete**

**Case 2:**
Element has exactly one child

- Splice the element out of the tree by connecting its parent to its successor.
Case 2:
Element has exactly one child

- Splice the element out of the tree by connecting its parent to its successor.
Case 2: Element has exactly one child

- Splice the element out of the tree by connecting its parent to its successor.
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
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
Binary Search Trees: Delete

Case 3:
Element has two children

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Binay Search Trees: Delete

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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
Algorithm 9 TreeDelete(z)

1: if left[z] = null or right[z] = null
2: then y ← z else y ← TreeSucc(z); select y to splice out
3: if left[y] ≠ null
4: then x ← left[y] else x ← right[y]; x is child of y (or null)
5: if x ≠ null then parent[x] ← parent[y]; parent[x] is correct
6: if parent[y] = null then
7: root[T] ← x
8: else
9: if y = left[parent[y]] then
10: left[parent[y]] ← x
11: else
12: right[parent[y]] ← x
13: if y ≠ z then copy y-data to z

fix pointer to x
All operations on a binary search tree can be performed in time $\Theta(h)$, where $h$ denotes the height of the tree.

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

With each insert- and delete-operation perform local adjustments to guarantee a height of $\Theta(\log n)$.

AVL-trees, Red-black trees, Scapegoat trees, 2-3 trees, B-trees, AA trees, Treaps

similar: SPLAY trees.
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 $O(\log n)$.

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Balanced Binary Search Trees

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

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.
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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
7.2 Red Black Trees

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

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.
7.2 Red Black Trees

Lemma 2

A *red-black tree* with \(n\) internal nodes has height at most \(\Theta(\log n)\).

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:

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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 2\(^{\text{bh}(v)}\) − 1 inner vertices.
7.2 Red Black Trees

Proof of Lemma 4.

Induction on the height of $v$. 

base case ($\text{height}(v) = 0$)

- If $\text{height}(v)$ (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 $2^{\text{bh}(v)} - 1$ inner vertices.
7.2 Red Black Trees

Proof of Lemma 4.

Induction on the height of $v$.

**base case ($\text{height}(v) = 0$)**

- If $\text{height}(v)$ (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.
7.2 Red Black Trees

Proof of Lemma 4.

Induction on the height of \( v \).

**base case** (\( \text{height}(v) = 0 \))

- If \( \text{height}(v) \) (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 \( 0 = 2^{\text{bh}(v)} - 1 \) inner vertices.
7.2 Red Black Trees

Proof of Lemma 4.

Induction on the height of $v$.

**base case** ($\text{height}(v) = 0$)

- If $\text{height}(v)$ (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 $0 = 2^{\text{bh}(v)} - 1$ inner vertices.
7.2 Red Black Trees

Proof (cont.)

induction step

Suppose $v$ is a node with height $bh(v) > 0$.

$v$ has two children with strictly smaller height. These children ($c_1$, $c_2$) either have $bh(c_i) = bh(v)$ or $bh(c_i) = bh(v) - 1$.

By induction hypothesis both sub-trees contain at least $2bh(v) - 1 - 1 = 2bh(v) - 2$ internal vertices.

Then $T_v$ contains at least $2(2bh(v) - 2) + 1 = 4bh(v) - 3$ vertices.
7.2 Red Black Trees

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.
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Proof (cont.)

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Proof (cont.)

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- Suppose \( v \) is a node with \( \text{height}(v) > 0 \).
- \( v \) has two children with strictly smaller height.
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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, $h \leq 2 \log(n + 1) = \Theta(\log n)$. \qed
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7.2 Red Black Trees

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.

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

Hence, $h \leq 2 \log(n + 1) = \mathcal{O}(\log n)$. \qed
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.
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:

LeftRotate(x)
RightRotate(z)
Red Black Trees: Insert

Insert:

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

RB-Insert(root, 18)

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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.
**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 its parent if:
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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
3:             uncle ← right[grandparent[z]]
4:             if col[uncle] = red then
5:                 col[p[z]] ← black; col[u] ← black;
6:                 col[gp[z]] ← red; z ← grandparent[z];
7:             else
8:                 if z = right[parent[z]] then
9:                     z ← p[z]; LeftRotate(z);
10:                col[p[z]] ← black; col[gp[z]] ← red;
11:                RightRotate(gp[z]);
12:         else same as then-clause but right and left exchanged
13:     col(root[T]) ← black;
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
5:             col[p[z]] ← black; col[u] ← black;
6:             col[gp[z]] ← red; z ← grandparent[z];
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Red Black Trees: Insert

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2: \( \textbf{if} \) parent\( [z] \) = left[gp\( [z] \)] \( \textbf{then} \)
3: \( \\text{uncle} \leftarrow \text{right[grandparent}[z] \]
4: \( \textbf{if} \) col[uncle] = red \( \textbf{then} \) Case 1: uncle red

5: \( \text{col}[p[z]] \leftarrow \text{black}; \text{col}[u] \leftarrow \text{black}; \)
6: \( \text{col}[gp[z]] \leftarrow \text{red}; z \leftarrow \text{grandparent}[z]; \)
7: \( \textbf{else} \)
8: \( \textbf{if} \) z = right[parent[z]] \( \textbf{then} \)
9: \( z \leftarrow p[z]; \text{LeftRotate}(z); \)
10: \( \text{col}[p[z]] \leftarrow \text{black}; \text{col}[gp[z]] \leftarrow \text{red}; \)
11: \( \text{RightRotate}(gp[z]); \)
12: \( \textbf{else} \) same as then-clause but right and left exchanged
13: \( \text{col}(\text{root}[T]) \leftarrow \text{black}; \)
Red Black Trees: Insert

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2: if parent[z] = left[gp[z]] then
3: uncle ← right[grandparent[z]]
4: if col[uncle] = red then
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
9: z ← p[z]; LeftRotate(z);
10: col[p[z]] ← black; col[gp[z]] ← red;
11: RightRotate(gp[z]);
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Red Black Trees: Insert

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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 1: Red Uncle

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7.2 Red Black Trees
Case 1: Red Uncle

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7.2 Red Black Trees

Ernst Mayr, Harald Räcke
Case 1: Red Uncle

1. recolour

Before:

```
A  B  C  D  E

z
```

After:

```
A  B  C  D  E

z
```

13

6

21

uncle
Case 1: Red Uncle

1. recolour

13

13

6

21

uncle

A

B

C

D

E

A

B

C

D

E

z

z

z
Case 1: Red Uncle

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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
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A  B  C  D  E
z
uncle
A  B
C
D  E

7.2 Red Black Trees
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3. you have a red black tree
Case 2a: Black uncle and z is right child

1. rotate around parent
2. move z downwards
3. you have Case 2b.
**Case 2a: Black uncle and z is right child**

1. rotate around parent
2. move z downwards
3. you have Case 2b.
Case 2a: Black uncle and $z$ is right child

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

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2. move z downwards
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Case 2a: Black uncle and \( z \) is right child

1. rotate around parent
2. move \( z \) downwards
3. you have Case 2b.
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 → Case 2b → red-black tree

- Case 2b → red-black tree

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

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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.
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Red Black Trees: Delete
Red Black Trees: Delete

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

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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
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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

Here $b$ is either black or red. If it is red we are in a special case that directly leads to a red-black tree.
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2. move fake black unit upwards
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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)
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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
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
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
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
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
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 $\Theta(\log n)$ times and every other step at most once, we get a red black tree. Hence, $\Theta(\log n)$ re-colorings and at most 3 rotations.
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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
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Splay Trees

\textbf{find} (\(\mathbf{x}\))

\begin{itemize}
  \item search for \(\mathbf{x}\) according to a search tree
  \item let \(\hat{\mathbf{x}}\) be last element on search-path
  \item splay(\(\hat{\mathbf{x}}\))
\end{itemize}
Splay Trees

$\text{insert}(x)$

- search for $x$; $\hat{x}$ is last visited element during search (successor or predecessor of $x$)
- $\text{splay}(\hat{x})$ moves $\hat{x}$ to the root
- insert $x$ as new root
delete($x$)

- search for $x$; splay($x$); remove $x$
- search largest element $\tilde{x}$ in $A$
- splay($\tilde{x}$) (on subtree $A$)
- connect root of $B$ as right child of $\tilde{x}$
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
better option \texttt{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)
Double Rotations

LeftRotate(y)

RightRotate(x)

DoubleRightRotate(x)

A
B
C
D

x
y
z
A
B
C
D

x
y
z
A
B
C
D

A
B
C
D

A
B
C
D

A
B
C
D

A
B
C
D
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)
Splay vs. Move to Root

7.3 Splay Trees
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Ernst Mayr, Harald Räcke
Splay vs. Move to Root

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7.3 Splay Trees

Ernst Mayr, Harald Räcke
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 $\mathcal{O}(\text{cost}(T_{\text{min}}))$, 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 $\Theta(\text{cost}(A, S))$, for processing $S$. 
Lemma 5

Splay Trees have an amortized running time of $O(\log n)$ for all operations.
**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 $\sum_i k_i \cdot t_i(n)$. 

7.3 Splay Trees
Potential Method

Introduce a potential for the data structure.

\[
\Phi(D_i) \quad \text{is the potential after the } i\text{-th operation.}
\]

Amortized cost of the \(i\)-th operation is

\[
\hat{c}_i = c_i + \Phi(D_i) - \Phi(D_{i-1}).
\]

Show that

\[
\Phi(D_i) \geq \Phi(D_0).
\]

Then

\[
k \sum_{i=1}^{k} c_i \leq k \sum_{i=1}^{k} \hat{c}_i + \Phi(D_k) - \Phi(D_0) = k \sum_{i=1}^{k} \hat{c}_i.
\]

This means the amortized costs can be used to derive a bound on the total cost.
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 $\hat{c}_i = c_i + \Phi(D_i) - \Phi(D_{i-1})$.

Show that $\Phi(D_i) \geq \Phi(D_0)$.

Then $\sum_{i=1}^{k} c_i \leq \sum_{i=1}^{k} \hat{c}_i = \sum_{i=1}^{k} c_i + \Phi(D_k) - \Phi(D_0)$.

This means the amortized costs can be used to derive a bound on the total cost.
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

$$\hat{c}_i = c_i + \Phi(D_i) - \Phi(D_{i-1}) .$$
Potential Method

Introduce a potential for the data structure.

- Φ(Dᵢ) is the potential after the i-th operation.
- Amortized cost of the i-th operation is

\[ \hat{c}_i = c_i + \Phi(D_i) - \Phi(D_{i-1}) \]

- Show that \( \Phi(D_i) \geq \Phi(D_0) \).
Potential Method

Introduce a potential for the data structure.

- $\Phi(D_i)$ is the potential after the $i$-th operation.
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- Show that $\Phi(D_i) \geq \Phi(D_0)$.

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$$\sum_{i=1}^{k} c_i \leq k \sum_{i=1}^{k} \hat{c}_i - \Phi(D_0).$$

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7.3 Splay Trees
**Potential Method**

Introduce a potential for the data structure.

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- Amortized cost of the $i$-th operation is

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$$\sum_{i=1}^{k} c_i \leq \sum_{i=1}^{k} c_i + \Phi(D_k) - \Phi(D_0)$$
Potential Method

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- $\Phi(D_i)$ is the potential after the $i$-th operation.
- Amortized cost of the $i$-th operation is

$$\hat{c}_i = c_i + \Phi(D_i) - \Phi(D_{i-1}).$$

- Show that $\Phi(D_i) \geq \Phi(D_0)$.

Then

$$\sum_{i=1}^{k} c_i \leq \sum_{i=1}^{k} c_i + \Phi(D_k) - \Phi(D_0) = \sum_{i=1}^{k} \hat{c}_i$$

This means the amortized costs can be used to derive a bound on the total cost.
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 $\text{pop}$ and $\text{multipop}$ do not generate an underflow.

Actual cost:

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

7.3 Splay Trees
Example: Stack

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Actual cost:

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

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

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 $\hat{C}_{\text{mp}} = C_{\text{mp}} + \Delta \Phi = \min\{\text{size}, k\} - \min\{\text{size}, k\} \leq 0$. 

7.3 Splay Trees
Example: Stack

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

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: Stack

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

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7.3 Splay Trees
Example: Stack

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

Amortized cost:

- $S. \text{push}()$: cost
  $$\hat{C}_{\text{push}} = C_{\text{push}} + \Delta \Phi = 1 + 1 \leq 2 .$$

- $S. \text{pop}()$: cost
  $$\hat{C}_{\text{pop}} = C_{\text{pop}} + \Delta \Phi = 1 - 1 \leq 0 .$$

- $S. \text{multipop}(k)$: cost
  $$\hat{C}_{\text{mp}} = C_{\text{mp}} + \Delta \Phi = \min\{\text{size}, k\} - \min\{\text{size}, k\} \leq 0 .$$
Example: Binary Counter

Incrementing a binary counter:
Consider a computational model where each bit-operation costs one time-unit.

...
Example: Binary Counter

Incrementing a binary counter:
Consider a computational model where each bit-operation costs one time-unit.

Incrementing an $n$-bit binary counter may require to examine $n$-bits, and maybe change them.

Actual cost:

- Changing bit from 0 to 1: cost 1.
- Changing bit from 1 to 0: cost 1.
- Increment: cost is $k + 1$, where $k$ is the number of consecutive ones in the least significant bit-positions (e.g., 001101 has $k = 1$).
Example: Binary Counter

Incrementing a binary counter:
Consider a computational model where each bit-operation costs one time-unit.

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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:
  \[
  \hat{C}_{0 \to 1} = C_{0 \to 1}^0 + \Delta \Phi = 1 + 1 \leq 2.
  \]

- Changing bit from 1 to 0:
  \[
  \hat{C}_{1 \to 0} = C_{1 \to 0}^1 - \Delta \Phi = 1 - 1 \leq 0.
  \]

- Increment: Let $k$ denotes the number of consecutive ones in the least significant bit-positions. An increment involves $k (1 \to 0)$-operations, and one $(0 \to 1)$-operation.

Hence, the amortized cost is $k + 1 + 1 = k + 2$.
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:

  $$\hat{C}_{0\to1} = C_{0\to1} + \Delta\Phi = 1 + 1 \leq 2.$$

- Changing bit from 1 to 0:

  $$\hat{C}_{1\to0} = C_{1\to0} + \Delta\Phi = 1 - 1 \leq 0.$$

- Increment: Let $k$ denotes the number of consecutive ones in the least significant bit-positions. An increment involves $k$ $(1 \to 0)$-operations, and one $(0 \to 1)$-operation.

Hence, the amortized cost is $k\hat{C}_{1\to0} + \hat{C}_{0\to1} \leq 2.$
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:**
  \[
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- **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 $k\hat{C}_{1\rightarrow0} + \hat{C}_{0\rightarrow1} \leq 2$. 
Example: Binary Counter

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

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

\[ \Delta \Phi = r'(x) + r'(p) - r(x) - r(p) \]
\[ = r'(p) - r(x) \]
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Splay: Zig Case

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

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

\[ \text{cost}_{\text{zig}} \leq 1 + 3(r'(x) - r(x)) \]
\[ \Delta \Phi = r'(x) + r'(p) + r'(g) - r(x) - r(p) - r(g) \]
\[ = r'(p) + r'(g) - r(x) - r(p) \]
\[ \leq r'(x) + r'(g) - r(x) - r(x) \]
\[ = r'(x) + r'(g) + r(x) - 3r'(x) + 3r'(x) - r(x) - 2r(x) \]
\[ = -2r'(x) + r'(g) + r(x) + 3(r'(x) - r(x)) \]
\[ \leq -2 + 3(r'(x) - r(x)) \quad \Rightarrow \text{cost}_{\text{zigzag}} \leq 3(r'(x) - r(x)) \]
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))
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\[
\leq -2 + 3(r'(x) - r(x)) \quad \Rightarrow \text{cost}_{\text{zigzag}} \leq 3(r'(x) - r(x))
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Splay: Zigzig Case

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\[ = -2r'(x) + r'(g) + r(x) + 3(r'(x) - r(x)) \]

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Splay: Zigzag Case

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

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

$= r'(p) + r'(g) - r(x) - r(p)$

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$\leq -2 + 3(r'(x) - r(x)) \Rightarrow \text{cost}_{\text{zigzig}} \leq 3(r'(x) - r(x))$
Splay: Zigzig Case

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

\[ = r'(p) + r'(g) - r(x) - r(p) \]

\[ \leq r'(x) + r'(g) - r(x) - r(x) \]

\[ = r'(x) + r'(g) + r(x) - 3r'(x) + 3r'(x) - r(x) - 2r(x) \]

\[ = -2r'(x) + r'(g) + r(x) + 3(r'(x) - r(x)) \]

\[ \leq -2 + 3(r'(x) - r(x)) \quad \Rightarrow \quad \text{cost}_{\text{zigzig}} \leq 3(r'(x) - r(x)) \]
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\[ \leq -2 + 3(r'(x) - r(x)) \]
\[ \rightarrow \text{cost}_{\text{zigzag}} \leq 3(r'(x) - r(x)) \]
Splay: Zigzig Case

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

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

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

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

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

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

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

= \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} \cdot \frac{s(x)}{s'(x)} + \frac{1}{2} \cdot \frac{s'(g)}{s'(x)} \right) \leq \log \left( \frac{1}{2} \right) = -1
Splay: Zigzag Case

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

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\[ \Delta \Phi = r'(x) + r'(p) + r'(g) - r(x) - r(p) - r(g) \]
\[ = r'(p) + r'(g) - r(x) - r(p) \]
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Splay: Zigzag Case

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

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

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\]
Amortized cost of the whole splay operation:

\[
\leq 1 + 1 + \sum_{\text{steps } t} 3(r_t(x) - r_{t-1}(x)) = 2 + r(\text{root}) - r_0(x) \leq \Theta(\log n)
\]
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.
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Augment an existing data-structure instead of developing a new one.
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
7.4 Augmenting Data Structures

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

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

4. How does find-by-rank work?

Find-by-rank($k$) := Select(root,$k$) with

Algorithm 7 Select($x$, $i$)
1: if $x$ = null then return error
2: if left[$x$] ≠ null then $r \leftarrow$ left[$x$].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[$x$], $i - r$)
Select\((x, i)\)

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
Select \((x, i)\)

Select \((25, 14)\)

Find-by-rank:
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7.4 Augmenting Data Structures
Select($x, i$)

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
Select \((x, i)\)

Select \((21, 5)\)

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
Select($x$, $i$)

Select(16, 5)

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
**Select**\((x, i)\)

**Select**\((19, 3)\)

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
Select($x, i$)

Select($20, 1$)

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

Ernst Mayr, Harald Räcke
7.4 Augmenting Data Structures

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

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.
7.4 Augmenting Data Structures

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

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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?

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**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 \textit{locally} from the size-fields of the children.
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 \(\infty\)
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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 \( \infty \)
7.5 $(a, b)$-trees

**Definition 7**
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2. every internal non-root vertex $v$ has at least $a$ and at most $b$ children
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7.5 \((a, b)\)-trees

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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 $k_d = \infty$. 
7.5 \((a, b)\)-trees

Example 8
7.5 \((a, b)\)-trees

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).
7.5 \((a, b)\)-trees

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Lemma 9

Let $T$ be an $(a, b)$-tree for $n > 0$ elements (i.e., $n + 1$ leaf nodes) and height $h$ (number of edges from root to a leaf vertex). Then

1. $2a^{h-1} \leq n + 1 \leq b^h$

2. $\log_b(n + 1) \leq h \leq 1 + \log_a\left(\frac{n+1}{2}\right)$

Proof.

If $n > 0$ the root has degree at least 2 and all other nodes have degree at least $a$. This gives that the number of leaf nodes is at least $2a^{h-1}$.

Analogously, the degree of any node is at most $b$ and, hence, the number of leaf nodes at most $b^h$. 

\[ \square \]
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1. \( 2a^{h-1} \leq n + 1 \leq b^h \)
2. \( \log_b(n + 1) \leq h \leq 1 + \log_a\left(\frac{n+1}{2}\right) \)

Proof.

If \( n > 0 \) the root has degree at least \( 2 \) and all other nodes have degree at least \( a \). This gives that the number of leaf nodes is at least \( 2a^{h-1} \).

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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.

7.5 $(a, b)$-trees
Search

Search(8)

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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($v$).
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7.5 $(a, b)$-trees

Ernst Mayr, Harald Räcke
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Rebalance($v$):

- Let $k_i$, $i = 1, \ldots, b$ denote the keys stored in $v$.
- Let $j := \lfloor \frac{b+1}{2} \rfloor$ 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 $\lfloor \frac{b-1}{2} \rfloor$ keys, and have therefore degree at least $\lfloor \frac{b-1}{2} \rfloor + 1 \geq a$ since $b \geq 2a - 1$.
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7.5 \((a, b)\)-trees
Insert

Insert(8)
Insert

Insert(8)
Insert

Insert(8)

7.5 $(a, b)$-trees
Insert

$\text{Insert}(8)$
Insert

Insert(8)
7.5 (a, b)-trees

Insert
Insert

Insert(6)

7.5 \((a, b)\)-trees
Insert

Insert(6)
Insert

Insert(6)
Insert

Insert(6)
Insert

Insert(7)

7.5 \((a, b)\)-trees
Insert

Insert(7)
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Insert(7)
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Insert(7)

7.5 \((a, b)\)-trees
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7.5 \((a, b)\)-trees
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$' (v)$. 

7.5 $(a, b)$-trees
Delete

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- If now the number of keys in $v$ is below $a - 1$ perform Rebalance' $(v)$. 
Delete

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.
Delete

Rebalance’(v):

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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.
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- If not: merge v with one of its neighbours.
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- 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.
Delete

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.
7.5 \((a, b)\)-trees
Delete

Delete(10)

7.5 \((a, b)\)-trees
Delete

Delete(10)

7.5 \((a, b)\)-trees
Delete (10)

7.5 \((a, b)\)-trees
7.5 \((a, b)\)-trees
Delete

Delete(14)

7.5 \((a, b)\)-trees
Delete

Delete(14)

7.5 \((a, b)\)-trees
Delete

Delete(14)

7.5 \((a, b)\)-trees
Delete (14)
Delete(14)
7.5 \((a, b)\)-trees
Delete(3)

7.5 \((a, b)\)-trees

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Delete

Delete(3)

\[ \begin{align*}
\text{Delete(3)} & \quad \begin{array}{c}
\text{1} \\
3 \\
19 \\
5 \\
28 \\
\infty
\end{array}
\end{align*} \]
Delete

**Delete(3)**

![Diagram of (a, b)-trees](image-url)
Delete $(3)$
Delete(3)
7.5 \((a, b)\)-trees
Delete

Delete(1)

\[ \begin{array}{c}
19 \\
1 5 \\
1 5 19 \\
1 \\
\end{array} \quad \begin{array}{c}
28 \\
19 28 \infty \\
19 28 \infty \\
\end{array} \]

7.5 \((a, b)\)-trees
Delete(1)
Delete (1)

7.5 \((a, b)\)-trees
7.5 \((a, b)\)-trees
Delete

Delete(19)

7.5 \((a, b)\)-trees
Delete(19)
Delete

Delete(19)

7.5 \((a, b)\text{-trees}\)
Delete

Delete (19)

7.5 \((a, b)\)-trees
Delete

Delete(19)

7.5 \((a, b)\)-trees
Delete(19)
(2, 4)-trees and red black trees

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

\[
\begin{array}{c}
17 \\
48 \\
4513 \\
13 \\
\end{array}
\begin{array}{c}
202541 \\
20227 \\
274347 \\
47 \\
\end{array}
\]

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

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

7.5 $(a, b)$-trees
There is a close relation between red-black trees and \((2, 4)\)-trees: 

```
1 3 5 11 13 18 19 22 27 43 47
17
4 8
20 25 41
```

Note that this correspondence is not unique. In particular, there are different red-black trees that correspond to the same \((2, 4)\)-tree.
There is a close relation between red-black trees and \((2, 4)\)-trees:

\[ \begin{align*}
&\text{17} \\
&\quad \downarrow \\
&\quad \begin{array}{c}
\text{4} & \text{8} \\
\downarrow & \downarrow \\
\text{1} & \text{3} \\
\quad \downarrow & \quad \downarrow \\
\text{5} & \text{11} & \text{13} \\
\quad \downarrow & \quad \downarrow \\
\text{18} & \text{19} \\
\quad \downarrow \\
\text{22} & \text{27} & \text{43} & \text{47} \\
\end{array}
\end{align*} \]

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

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

\begin{center}
\begin{tikzpicture}
  \node (root) {17};
  \node (left) at (root -| 0,0) {4 \node[red] {8}};
  \node (right) at (root -| 1,0) {20 \node[red] {25} \node[red] {41}};
  \node (leftchild) at (-1,0) {1 \node[red] {3}};\node[gray] at (-1.5,0) {5};\node[gray] at (-1.25,0) {11} \node[gray] at (-1.1,0) {13};
  \node (rightchild) at (1,0) {18 \node[red] {19}};\node[gray] at (1.5,0) {22};\node[gray] at (1.1,0) {27};\node[gray] at (1.25,0) {43} \node[gray] at (1.5,0) {47};
  \draw[->] (root) -- (left);
  \draw[->] (root) -- (right);
  \draw[->] (left) -- (leftchild);
  \draw[->] (left) -- (rightchild);
  \draw[->] (right) -- (rightchild);
\end{tikzpicture}
\end{center}

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

There is a close relation between red-black trees and (2, 4)-trees:
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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. $\Theta(n)$
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How can we improve the search-operation?
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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: $|L_1| + |L_0| = |L_1| (ignoring additive constants)$

Choose $|L_1| = \sqrt{n}$. Then search time $\Theta(\sqrt{n})$. 
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\[ \text{Diagram showing skip list with express lane.} \]
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Choose $|L_1| = \sqrt{n}$. Then search time $\Theta(\sqrt{n})$. 
Add more express lanes. Lane $L_i$ contains roughly every $\frac{L_{i-1}}{L_i}$-th item from list $L_{i-1}$.
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Search(x) ($k + 1$ lists $L_0, \ldots, L_k$)
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**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.
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- ...  
- At most $|L_k| + \sum_{i=1}^{k} \frac{L_{i-1}}{L_i} + 3(k + 1)$ steps.
Choose ratios between list-lengths evenly, i.e., \( \frac{|L_{i-1}|}{|L_i|} = r \), and, hence, \( L_k \approx r^{-k}n \).
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7.6 Skip Lists

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

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

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

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

\[
\begin{align*}
  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}} \\
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7.6 Skip Lists

Ernst Mayr, Harald Räcke
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\]

Choosing \( k = \Theta(\log n) \) gives a logarithmic running time.
7.6 Skip Lists

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!
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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.
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High Probability

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

Here the $\mathcal{O}$-notation hides a constant that may depend on $\alpha$. 
Definition 10 (High Probability)

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

Suppose there are a 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 $O(\log n)$).
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Then the probability that all $E_i$ hold is at least

$$\Pr[E_1 \land \cdots \land E_\ell]$$
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Then the probability that all $E_i$ hold is at least

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

-∞ 5 8 10 12 14 18 23 26 28 35 43 ∞
7.6 Skip Lists

Backward analysis:

At each point the path goes up with probability $\frac{1}{2}$ and left with probability $\frac{1}{2}$.

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.
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At each point the path goes up with probability $\frac{1}{2}$ and left with probability $\frac{1}{2}$.

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.
7.6 Skip Lists

Backward analysis:

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

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\[ \left( \frac{n}{k} \right)^k \leq \binom{n}{k} \leq \left( \frac{en}{k} \right)^k \]
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\binom{n}{k} = \frac{n!}{k! \cdot (n - k)!}
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\[ \binom{n}{k} = \frac{n!}{k! \cdot (n-k)!} = \frac{n \cdot \ldots \cdot (n-k+1)}{k \cdot \ldots \cdot 1} \]
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7.6 Skip Lists
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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.
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7.6 Skip Lists

\[ \Pr[E_{z,k}] \]
Pr[$E_{z,k}$] ≤ Pr[at most $k$ heads in $z$ trials]
7.6 Skip Lists

\[\Pr[E_{z,k}] \leq \Pr[\text{at most } k \text{ heads in } z \text{ trials}]\]

\[\leq \binom{z}{k} 2^{-(z-k)}\]
Pr[$E_{z,k}$] ≤ Pr[at most $k$ heads in $z$ trials]

\[ \leq \left( \frac{z}{k} \right)^{2^{-z-k}} \leq \left( \frac{ez}{k} \right)^k 2^{-(z-k)} \]
7.6 Skip Lists

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choosing $k = \gamma \log n$ with $\gamma \geq 1$ and $z = (\beta + \alpha)\gamma \log n$
7.6 Skip Lists

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\[ \leq \left( \frac{2e(\beta + \alpha)}{2\beta} \right)^k n^{-\alpha} \]
7.6 Skip Lists

\[ \Pr[E_{z,k}] \leq \Pr[\text{at most } k \text{ heads in } z \text{ trials}] \]

\[ \leq \left( \frac{z}{k} \right)^{2^{-(z-k)}} \leq \left( \frac{ez}{k} \right)^k 2^{-(z-k)} \leq \left( \frac{2ez}{k} \right)^k 2^{-z} \]

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\[ \leq \left( \frac{2e(\beta + \alpha)}{2^\beta} \right)^k n^{-\alpha} \]

now choosing \( \beta = 6\alpha \) gives
7.6 Skip Lists

\[ \Pr[E_{z,k}] \leq \Pr[\text{at most } k \text{ heads in } z \text{ trials}] \]

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now choosing \( \beta = 6 \alpha \) gives

\[ \leq \left( \frac{42 \alpha}{64 \alpha} \right)^{k} n^{-\alpha} \]
7.6 Skip Lists

\[ \Pr[E_{z,k}] \leq \Pr[\text{at most } k \text{ heads in } z \text{ trials}] \]

\[ \leq \binom{z}{k} 2^{-(z-k)} \leq \left( \frac{ez}{k} \right)^k 2^{-(z-k)} \leq \left( \frac{2ez}{k} \right)^k 2^{-z} \]

choosing \( k = \gamma \log n \) with \( \gamma \geq 1 \) and \( z = (\beta + \alpha)\gamma \log n \)

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for \( \alpha \geq 1 \).
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 $\Pr[A_{k+1}] \leq n^{2 - (k + 1)} \leq n - \gamma - 1$.

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,

$$\Pr[\text{search requires } z \text{ steps}] \leq \Pr[E_{z,k}] + \Pr[A_{k+1}] \leq n - \alpha + n - (\gamma - 1)$$

This means, the search requires at most $z$ steps, w.h.p.
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\leq n^{-\alpha} + n^{-(\gamma-1)}
\]

This means, the search requires at most \( z \) steps, w. h. p.
7.7 Hashing

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 $\text{key}[e] = k$ in $S$ if it exists; otherwise return 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 directly compute the memory location from the given key. The goal is to have constant search time.
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7.7 Hashing

Definitions:

- Universe $U$ of keys, e.g., $U \subseteq \mathbb{N}_0$. $U$ very large.
- Set $S \subseteq U$ of keys, $|S| = m \leq |U|$.
- Array $T[0,\ldots,n-1]$ hash-table.
- Hash function $h : U \to [0,\ldots,n-1]$.

The hash-function $h$ should fulfill:

- Fast to evaluate.
- Small storage requirement.
- Good distribution of elements over the whole table.
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Direct Addressing

Ideally the hash function maps all keys to different memory locations.

This special case is known as 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 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.
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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 $f: U \to [0, \ldots, n - 1]$. 

7.7 Hashing
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Ernst Mayr, Harald Räcke
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Proof.

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

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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.
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.
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

Arrange elements that map to the same position in a linear list.

- Access: compute $h(x)$ and search list for $key[x]$.
- Insert: insert at the front of the list.
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

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The time required for an unsuccessful search is 1 plus the length of the list that is examined. The average length of a list is $\alpha = \frac{m}{n}$. Hence, if $A$ is the collision resolving strategy “Hashing with Chaining” we have

$$A^- = 1 + \alpha.$$
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, $\Pr[X_{ij} = 1] = 1/n$ for uniform hashing.

The expected successful search cost is

$$
\mathbb{E}\left[ \frac{1}{m} \sum_{i=1}^{m} \left( 1 + \sum_{j=i+1}^{m} X_{ij} \right) \right]
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cost for key $k_i$
Hashing with Chaining

\[ E \left[ \frac{1}{m} \sum_{i=1}^{m} \left( 1 + \sum_{j=i+1}^{m} X_{ij} \right) \right] \]
Hashing with Chaining

\[
E \left[ \frac{1}{m} \sum_{i=1}^{m} \left( 1 + \sum_{j=i+1}^{m} X_{ij} \right) \right] = \frac{1}{m} \sum_{i=1}^{m} \left( 1 + \sum_{j=i+1}^{m} E[X_{ij}] \right)
\]

Hence, the expected cost for a successful search is

\[
\frac{A}{m} \leq 1 + \alpha^2 - \alpha^2 m.
\]
Hashing with Chaining

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7.7 Hashing
Hashing with Chaining

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= 1 + \frac{1}{mn} \sum_{i=1}^{m} (m - i)
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Hence, the expected cost for a successful search is \( A^+ \leq 1 + \frac{\alpha}{2} \).
Hashing with Chaining

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.
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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:**
  \[ h(k, i) = h(k) + c_1i + c_2i^2 \mod n. \]

- **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).
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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)
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\[
L^- \approx \frac{1}{2} \left( 1 + \frac{1}{(1 - \alpha)^2} \right)
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Let $L$ be the method of linear probing for resolving collisions:

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

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

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

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

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

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\]
Double Hashing

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

Lemma 15

\( A \) be the method of double hashing for resolving collisions:

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

\[
D^- \approx \frac{1}{1 - \alpha}
\]
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:

$$D^+ \approx \frac{1}{\alpha} \ln \left( \frac{1}{1 - \alpha} \right)$$

$$D^- \approx \frac{1}{1 - \alpha}$$
Open Addressing

Some values:

<table>
<thead>
<tr>
<th>( \alpha )</th>
<th><strong>Linear Probing</strong></th>
<th><strong>Quadratic Probing</strong></th>
<th><strong>Double Hashing</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( L^+ )</td>
<td>( L^- )</td>
<td>( Q^+ )</td>
</tr>
<tr>
<td>0.5</td>
<td>1.5</td>
<td>2.5</td>
<td>1.44</td>
</tr>
<tr>
<td>0.9</td>
<td>5.5</td>
<td>50.5</td>
<td>2.85</td>
</tr>
<tr>
<td>0.95</td>
<td>10.5</td>
<td>200.5</td>
<td>3.52</td>
</tr>
</tbody>
</table>
Open Addressing

\[ \alpha \text{ probes} \]

\[ L^- - Q^- - D^- \]

\[ L^+ - Q^+ - D^+ \]

7.7 Hashing

Ernst Mayr, Harald Räcke
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.

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

$$
\Pr[X \geq i] = mn \cdot m^{n-1} \cdot m^{n-2} \cdot \cdots \cdot m^{n-i+2} \leq (mn)^{i-1} = \alpha_{i-1}.
$$
Analysis of Idealized Open Address Hashing

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

$$\Pr[A_1 \cap A_2 \cap \cdots \cap A_{i-1}]$$
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.

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

$$\Pr[X \geq i] = \frac{m^n}{m^n - 1^{n-1} \cdot m^{n-2} \cdot \ldots \cdot m^{n-i+2}} \leq \left(\frac{m^n}{m^n}ight)^{i-1} = \alpha^{i-1}.$$
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\]

\[
\Pr[X \geq i]
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$$\Pr[X \geq i] = \frac{m}{n} \cdot \frac{m-1}{n-1} \cdot \frac{m-2}{n-2} \cdots \cdot \frac{m-i+2}{n-i+2}$$
Analysis of Idealized Open Address Hashing

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\]

\[
Pr[X \geq i] = \frac{m}{n} \cdot \frac{m-1}{n-1} \cdot \frac{m-2}{n-2} \cdots \cdots \frac{m-i+2}{n-i+2} \\
\leq \left(\frac{m}{n}\right)^{i-1}
\]
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\]

\[
\leq \left( \frac{m}{n} \right)^{i-1} = \alpha^{i-1}.
\]
Analysis of Idealized Open Address Hashing
Analysis of Idealized Open Address Hashing

\[ E[X] = \sum_{i=1}^{\infty} \Pr[X \geq i] \]
Analysis of Idealized Open Address Hashing

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\[ \frac{1}{1 - \alpha} = 1 + \alpha + \alpha^{2} + \alpha^{3} + \ldots \]
Analysis of Idealized Open Address Hashing

\[ \sum_i i \Pr[X = i] = \sum_i \Pr[X \geq i] \]

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 \( i = 1, 2, ..., j \).)
Analysis of Idealized Open Address Hashing

\[ i = 1 \]

\[
\sum_i i \Pr[X = i] = \sum_i \Pr[X \geq i]
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Analysis of Idealized Open Address Hashing

\[ i = 2 \]

\[ \sum_i i \Pr[X = i] = \sum_i \Pr[X \geq i] \]

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Analysis of Idealized Open Address Hashing

\( i = 3 \)

\[
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7.7 Hashing
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

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 $1 - \frac{i}{n} = \frac{n}{n - i}$.

$$1 - \frac{i}{n} \leq 1 - \frac{1}{\alpha} \int_{n-m+1}^{n} x \, dx = 1 - \frac{1}{\alpha} \ln \frac{n}{n-m}$$
Analysis of Idealized Open Address Hashing

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.
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\[
\frac{1}{m} \sum_{i=0}^{m-1} \frac{n}{n-i} = \frac{n}{m} \sum_{i=0}^{m-1} \frac{1}{n-i} = \frac{1}{\alpha} \sum_{k=n-m+1}^{n} \frac{1}{k}
\]
Analysis of Idealized Open Address Hashing

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\]

\[
\leq \frac{1}{\alpha} \int_{n-m}^{n} \frac{1}{x} \, dx
\]
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\[
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Analysis of Idealized Open Address Hashing

\[ f(x) = \frac{1}{x} \]

\[ \sum_{k=m-n+1}^{n} \frac{1}{k} \leq \int_{m-n}^{n} \frac{1}{x} \, dx \]

7.7 Hashing
Deletions in Hashtables

How do we delete in a hash-table?

- For hashing with chaining this is not a problem. Simply search for the key, and delete the item in the corresponding list.

- For open addressing this is difficult.
Deletions in Hashtables

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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.
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Deletions for Linear Probing

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Deletions for Linear Probing

\begin{algorithm}
   \textbf{Algorithm 12} delete\((p)\)
   \begin{align*}
   1: & \quad T[p] \leftarrow \text{null} \\
   2: & \quad p \leftarrow \text{succ}(p) \\
   3: \quad \textbf{while} \quad T[p] \neq \text{null} \quad \textbf{do} \\
   4: & \quad y \leftarrow T[p] \\
   5: & \quad T[p] \leftarrow \text{null} \\
   6: & \quad p \leftarrow \text{succ}(p) \\
   7: & \quad \text{insert}(y)
   \end{align*}
\end{algorithm}

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

Pointers into the hash-table become invalid.
Deletions for Linear Probing

Algorithm 12 delete($p$)

1: $T[p] \leftarrow$ null
2: $p \leftarrow$ succ($p$)
3: while $T[p] \neq$ null do
4: $y \leftarrow T[p]$
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$p$ is the index into the table-cell that contains the object to be deleted.

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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 \( \mathcal{H} \).
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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 $\mathcal{H}$.
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 $\frac{1}{n}$. 
Universal Hashing

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Universal Hashing

**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:

- 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.

- For all $u_1, u_2 \in U$ with $u_1 \neq u_2$, and for any two hash-positions $t_1, t_2$:

  $$\Pr[h(u_1) = t_1 \land h(u_2) = t_2] \leq \frac{1}{n^2}.$$ 

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

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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

- 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.
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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 $\mathcal{H}$. 
**Definition 19**

A class \( \mathcal{H} \) of hash-functions from the universe \( U \) into the set \( \{0, \ldots, n - 1\} \) is called \((\mu, k)\)-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 \( t_1, \ldots, t_\ell \):

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

where the probability is w. r. t. the choice of a random hash-function from set \( \mathcal{H} \).
Let $U := \{0, \ldots, p - 1\}$ for a prime $p$. Let $\mathbb{Z}_p := \{0, \ldots, p - 1\}$, and let $\mathbb{Z}_p^* := \{1, \ldots, p - 1\}$ denote the set of invertible elements in $\mathbb{Z}_p$.

Define

$$h_{a,b}(x) := (ax + b \mod p) \mod n$$

**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 $\{0, \ldots, n - 1\}$. 

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**Universal Hashing**
Universal Hashing

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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 $1/n$.

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).
Universal Hashing

**Proof.**

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

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Universal Hashing

- 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 \(t_y := ay + b\).
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This holds because we can compute \(a\) and \(b\) when given \(t_x\) and \(t_y\):
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\begin{align*}
t_x &\equiv ax + b \pmod{p} \\
t_y &\equiv ay + b \pmod{p}
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Universal Hashing

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t_x \equiv ax + b \pmod{p} \\
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\]

\[
t_x - t_y \equiv a(x - y) \pmod{p} \\
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\]
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This holds because we can compute \(a\) and \(b\) when given \(t_x\) and \(t_y\):

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

There is a one-to-one correspondence between hash-functions (pairs \((a, b), a \neq 0\)) and pairs \((t_x, t_y), t_x \neq t_y\).

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 \([p/n]\) values.
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Universal Hashing

As \( t_y \neq t_x \) there are

\[
\frac{\lceil p^n \rceil - 1}{n - 1} \leq p^n + n - 1 \leq p - 1
\]

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

This happens with probability at most \( \frac{1}{n} \).
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As \( t_y \neq t_x \) there are

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\left\lceil \frac{p}{n} \right\rceil - 1 \leq \frac{p}{n} + \frac{n-1}{n} - 1 \leq \frac{p-1}{n}
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As $t_Y \neq t_X$ there are

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possibilities for choosing $t_Y$ such that the final hash-value creates a collision.

This happens with probability at most $\frac{1}{n}$. 
Universal Hashing

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

$$\left\lfloor \frac{p}{n} \right\rfloor^2 \leq \Pr x \neq ty \in \mathbb{Z}_2 \left[ t_x \mod n = h_1 \land t_y \mod n = h_2 \right] \leq \left\lceil \frac{p}{n} \right\rceil^2 p(p-1)$$

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 $\left\lceil \frac{p}{n} \right\rceil$. 7.7 Hashing
Universal Hashing

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

$$\Pr_{t_x \neq t_y \in \mathbb{Z}_p^2} \left[ \begin{array}{c} t_x \mod n = h_1 \\ ^\wedge \\ t_y \mod n = h_2 \end{array} \right]$$
Universal Hashing

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

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

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

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

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 $\left\lceil \frac{p}{n} \right\rceil$. 

7.7 Hashing

Ernst Mayr, Harald Räcke
Definition 21

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

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

Let $\mathcal{H}_n^d := \{h_{\bar{a}} | \bar{a} \in \{0, \ldots, q - 1\}^{d+1}\}$. 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

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

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

The polynomial is defined by $d + 1$ distinct points.
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The polynomial is defined by $d + 1$ distinct points.
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 $A_\ell = \{ h_\bar{a} \in \mathcal{H} \mid h_\bar{a}(x_i) = t_i \text{ for all } i \in \{1, \ldots, \ell\} \}$

Then

$$h_\bar{a} \in A_\ell \iff h_\bar{a} = f_\bar{a} \mod n \text{ and }$$

$$f_\bar{a}(x_i) \in \{ t_i + \alpha \cdot n \mid \alpha \in \{0, \ldots, \lceil \frac{q}{n} \rceil - 1\} \}$$

=: $B_i$

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

$$|B_1| \cdot \ldots \cdot |B_\ell|$$

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

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\[
   h_{\bar{a}} \in A^\ell \iff h_{\bar{a}} = f_{\bar{a}} \mod n \text{ and } f_{\bar{a}}(x_i) \in \{t_i + \alpha \cdot n \mid \alpha \in \{0, \ldots, \left\lfloor \frac{q}{n} \right\rfloor - 1\}\}
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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 $A^\ell = \{h_\alpha \in \mathcal{H} \mid h_\alpha(x_i) = t_i \text{ for all } i \in \{1, \ldots, \ell\}\}$

Then

$$h_\alpha \in A^\ell \iff h_\alpha = f_\alpha \mod n \text{ and } f_\alpha(x_i) \in \{t_i + \alpha \cdot n \mid \alpha \in \{0, \ldots, \left\lfloor \frac{q}{n} \right\rfloor - 1\}\} =: B_i$$

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

$$|B_1| \cdot \ldots \cdot |B_\ell|$$

possibilities to do this (so that $h_\alpha(x_i) = t_i$).
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 $A^\ell = \{ h_\bar{a} \in \mathcal{H} \mid h_\bar{a}(x_i) = t_i \text{ for all } i \in \{1, \ldots, \ell\} \}$

Then $h_\bar{a} \in A^\ell \Leftrightarrow h_\bar{a} = f_\bar{a} \mod n$ and

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

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

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

We have

$$|B_1| \cdot \ldots \cdot |B_\ell|$$

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

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

\[
|B_1| \cdot \ldots \cdot |B_\ell| \cdot q^{d-\ell+1} \leq \left\lceil \frac{q}{n} \right\rceil^\ell \cdot q^{d-\ell+1}
\]

possibilities to choose \( \bar{a} \) such that \( h\bar{a} \in A_\ell \).
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Universal Hashing

Therefore the probability of choosing $h_\bar{a}$ from $A_\ell$ is only

$$\left\lceil \frac{q}{n} \right\rceil^\ell \cdot \frac{q^{d-\ell+1}}{q^{d+1}}$$
Therefore the probability of choosing \( h_{\tilde{a}} \) from \( A_\ell \) is only

\[
\left( \frac{q}{n} \right)^\ell \cdot \frac{q^{d-\ell+1}}{q^{d+1}} \leq \frac{(q+n)^\ell}{q^\ell}
\]

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

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

Therefore the probability of choosing $h_{\bar{a}}$ from $A_\ell$ is only

$$\frac{\left\lfloor \frac{q}{n} \right\rfloor^\ell \cdot q^{d-\ell+1}}{q^{d+1}} \leq \frac{(\frac{q+n}{n})^\ell}{q^\ell} \leq \left(\frac{q+n}{q}\right)^\ell \cdot \frac{1}{n^\ell}$$
Therefore the probability of choosing $h_{\bar{a}}$ from $A_\ell$ is only

$$\frac{\left\lceil \frac{q}{n} \right\rceil \ell \cdot q^{d-\ell+1}}{q^{d+1}} \leq \frac{(q+n)^\ell}{q^\ell} \leq \left(\frac{q+n}{q}\right)^\ell \cdot \frac{1}{n^\ell}$$

$$\leq \left(1 + \frac{1}{\ell}\right)^\ell \cdot \frac{1}{n^\ell}$$
Universal Hashing

Therefore the probability of choosing $h_{\bar{a}}$ from $A_{\ell}$ is only

$$\frac{\left[\frac{q}{n}\right]^{\ell} \cdot q^{d-\ell+1}}{q^{d+1}} \leq \frac{(\frac{q+n}{n})^{\ell}}{q^{\ell}} \leq \left(\frac{q+n}{q}\right)^{\ell} \cdot \frac{1}{n^{\ell}}$$

$$\leq \left(1 + \frac{1}{\ell}\right)^{\ell} \cdot \frac{1}{n^{\ell}} \leq \frac{e}{n^{\ell}}.$$
Therefore the probability of choosing $h_{\bar{a}}$ from $A_\ell$ is only

$$\frac{\left\lceil \frac{q}{n} \right\rceil \ell \cdot q^{d-\ell+1}}{q^{d+1}} \leq \frac{(q+n)^\ell}{n q^\ell} \leq \left( \frac{q+n}{q} \right)^\ell \cdot \frac{1}{n^\ell}$$

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

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

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

7.7 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.
Perfect Hashing

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

\[
E[\#\text{Collisions}] = \binom{m}{2} \cdot \frac{1}{n}.
\]

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 \( \frac{1}{2} \).
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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.
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Perfect Hashing

\[ \sum_i m_i = m \]
Perfect Hashing

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

$$E\left[\sum j m^2\right] = 2 E\left[\sum j (m_j^2)\right] + E\left[\sum j m_j\right]$$

The first expectation is simply the expected number of collisions, for the first level. Since we use universal hashing we have $E = 2 (m^2) 1 m + m = 2 m - 1$. 

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Perfect Hashing

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$$E\left[ \sum_j m_j^2 \right]$$
Perfect Hashing

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

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

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

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

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

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

Two hash-tables $T_1[0,...,n-1]$ and $T_2[0,...,n-1]$, 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.
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- A search clearly takes constant time if the above constraint is met.
Cuckoo Hashing

Insert:

$T_1$:
- $\emptyset$
- $\emptyset$
- $x_7$
- $\emptyset$
- $x_4$
- $x_1$
- $\emptyset$
- $\emptyset$

$T_2$:
- $\emptyset$
- $\emptyset$
- $x_9$
- $\emptyset$
- $\emptyset$
- $x_6$
- $x_3$
- $\emptyset$

7.7 Hashing
Cuckoo Hashing

Insert:

\[ T_1 \]

\[ x \]

\[ x_7 \]

\[ T_2 \]

\[ x_9 \]

\[ x_6 \]

\[ x_3 \]
Cuckoo Hashing

Insert:

\[\emptyset \quad \emptyset \quad x_1 \quad x_4 \quad \emptyset \quad \emptyset \quad x_7 \quad \emptyset \quad \emptyset \quad \emptyset \quad x_3 \quad x_6 \quad \emptyset \]

\[T_1 \quad T_2\]
Cuckoo Hashing

Insert:

\[
\begin{align*}
\{\emptyset, \emptyset, \emptyset, x_4, x_1, \emptyset, \emptyset\} & \quad \text{for } T_1 \\
\{\emptyset, \emptyset, x_9, \emptyset, \emptyset, x_3, \emptyset\} & \quad \text{for } T_2
\end{align*}
\]

Nodes: \(x, x_4, x_1, x_6, x_7\)
Cuckoo Hashing

Insert:

```
T1
\[\emptyset\]
\[\emptyset\]
\[\emptyset\]
\[x_4\]
\[x_6\]
\[\emptyset\]
\[\emptyset\]

T2
\[\emptyset\]
\[\emptyset\]
\[\emptyset\]
\[x_9\]
\[x_7\]
\[\emptyset\]
\[\emptyset\]
```

7.7 Hashing
Ernst Mayr, Harald Räcke
Cuckoo Hashing

Algorithm 13 Cuckoo-Insert(x)
1: if \(T_1[h_1(x)] = x \lor T_2[h_2(x)] = x\) then return
2: steps ← 1
3: while steps ≤ maxsteps do
4: exchange \(x\) and \(T_1[h_1(x)]\)
5: if \(x = null\) then return
6: exchange \(x\) and \(T_2[h_2(x)]\)
7: if \(x = null\) then return
8: steps ← steps + 1
9: rehash() // change hash-functions; rehash everything
10: Cuckoo-Insert(x)
Cuckoo Hashing

- We call one iteration through the while-loop a **step** of the algorithm.
- We call a sequence of iterations through the while-loop without the termination condition becoming true a **phase** of the algorithm.
- We say a phase is **successful** if it is not terminated by the maxstep-condition, but the while loop is left because $x = \text{null}$.
Cuckoo Hashing

- We call one iteration through the while-loop a step of the algorithm.
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We call one iteration through the while-loop a **step** of the algorithm.

We call a sequence of iterations through the while-loop without the termination condition becoming true a **phase** of the algorithm.

We say a phase is **successful** if it is not terminated by the `maxstep`-condition, but the while loop is left because `x = 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?
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 $\text{maxsteps}$ steps).

Formally what is the probability to enter an infinite loop that touches $s$ different keys?
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What is the expected time for an insert-operation?

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

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

\[ T_1 \]

\[ T_2 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

7.7 Hashing

Ernst Mayr, Harald Räcke
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ x_2 \]

\[ T_2 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ x = x_1 \rightarrow x_1 \rightarrow x_2 \rightarrow x_2 \]

\[ x = x_1 \rightarrow x_2 \rightarrow x_3 \]

\[ T_1 \rightarrow x_3 \rightarrow T_2 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ x_1 \]

\[ x_3 \]

\[ T_2 \]

\[ x_2 \]

\[ x_2 \]

\[ x_3 \]

\[ x_4 \]
Cuckoo Hashing: Insert

\[ x = x_1 \rightarrow x_1 \rightarrow x_3 \rightarrow x_5 \rightarrow x_2 \rightarrow x_4 \rightarrow x_2 \]

\[ T_1 \rightarrow T_2 \]

7.7 Hashing
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ x = x_2 \]

\[ T_2 \]

\[ x_1 \]

\[ x_3 \]

\[ x_5 \]

\[ x_2 \]

\[ x_4 \]

\[ x_6 \]
Cuckoo Hashing: Insert

\[ x = x_1 \rightarrow x_1 \]

\[ x_3 \rightarrow x_5 \rightarrow x_4 \rightarrow x_6 \rightarrow x_7 \]

\[ T_1 \rightarrow x_7 \rightarrow T_2 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ x_1 \rightarrow x_2 \]
\[ x_3 \rightarrow x_4 \]
\[ x_5 \rightarrow x_6 \]
\[ x_7 \rightarrow x_8 \]

\[ T_1 \rightarrow T_2 \]

7.7 Hashing
Cuckoo Hashing: Insert

\[ x = x_1 \]

[Diagram showing the process of cuckoo hashing with arrows indicating the movement of elements between two tables, \( T_1 \) and \( T_2 \), and a variable \( x \) being inserted and placed at index 1.]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ x_1 \]

\[ x_2 \]

\[ x_3 \]

\[ x_4 \]

\[ x_5 \]

\[ x_6 \]

\[ x_7 \]

\[ x_8 \]

\[ T_2 \]

7.7 Hashing
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ T_2 \]

7.7 Hashing
Cuckoo Hashing: Insert
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\[ x = x_1 \]

\[ x_9 \]
\[ x_2 \]
\[ x_4 \]
\[ x_5 \]
\[ x_7 \]
\[ T_1 \]

\[ x_10 \]
\[ x_9 \]
\[ x_3 \]
\[ x_2 \]
\[ x_5 \]
\[ x_8 \]
\[ T_2 \]

\[ x_11 \]

7.7 Hashing
Cuckoo Hashing: Insert

The diagram illustrates the process of inserting elements into a Cuckoo Hash table. Each element is represented by a node and is hashed into two possible positions, denoted by $T_1$ and $T_2$. In case of a collision, the table uses a probing sequence to find an empty slot.
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ x = x_2 \]

\[ x = x_3 \]

\[ x = x_4 \]

\[ x = x_5 \]

\[ x = x_6 \]

\[ x = x_7 \]

\[ x = x_8 \]

\[ x = x_9 \]

\[ x = x_{10} \]

\[ x = x_{11} \]

\[ x = x_{12} \]
Cuckoo Hashing: Insert

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

- $s$ different cells (alternating blue cells from $T_1$ and red cells from $T_2$).
- $s$ distinct keys $x_1, x_2, ..., x_s$, 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.
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.
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- One link represents key $x$; this is where the counting starts.
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Cuckoo Hashing

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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 $s \geq 3$. 
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

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**Observation:**
If during a phase the insert-procedure runs into a cycle there must exist an active cycle structure of size $s \geq 3$. 
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 $\frac{\mu}{n^3}$ 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 $\frac{\mu}{n^3}$ since $h_2$ is a $(\mu, s)$-independent hash-function.

These events are independent.
Cuckoo Hashing

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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 $\frac{\mu}{ns}$ since $h_1$ is a $(\mu, s)$-independent hash-function.

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Cuckoo Hashing

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

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Cuckoo Hashing

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Cuckoo Hashing

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 $x$.

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Cuckoo Hashing

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Cuckoo Hashing

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

\[
\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}}
\]
Cuckoo Hashing

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

$$\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} = \frac{\mu^2}{n m} \sum_{s=3}^{\infty} s^3 \left( \frac{m}{n} \right)^s$$
Cuckoo Hashing

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

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\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} = \frac{\mu^2}{nm} \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
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\leq \frac{\mu^2}{m^2} \sum_{s=3}^{\infty} s^3 \left( \frac{1}{1 + \epsilon} \right)^s \leq \Theta \left( \frac{1}{m^2} \right).
\]
Cuckoo Hashing

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\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 \((1 + \epsilon)m \leq n\).
Cuckoo Hashing

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

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

Hence,

\[ \Pr[\text{cycle}] = O \left( \frac{1}{m^2} \right). \]
Now, we analyze the probability that a phase is not successful without running into a closed cycle.
Cuckoo Hashing

Sequence of visited keys:
\[ x = x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_3, x_2, x_1 = x, x_8, x_9, \ldots \]
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.
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**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.*
Cuckoo Hashing

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.
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A path-structure of size $s$ is defined by

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Cuckoo Hashing
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Cuckoo Hashing

Ernst Mayr, Harald Räcke
Cuckoo Hashing

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

Observation:
If a phase takes at least $t$ steps without running into a cycle there must exist an active path-structure of size $(2t + 2)/3$. 
Cuckoo Hashing

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

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

The probability that there exists an active path-structure of size $s$ is at most

$$2 \cdot n^{s+1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}}$$
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$$2 \cdot n^{s+1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} \leq 2\mu^2 \left(\frac{m}{n}\right)^{s-1}$$
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Plugging in $s = (2t + 2)/3$ gives
Cuckoo Hashing

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$$\leq 2\mu^2 \left(\frac{1}{1 + \epsilon}\right)^{(2t+2)/3-1} = 2\mu^2 \left(\frac{1}{1 + \epsilon}\right)^{(2t-1)/3}.$$
We choose $\text{maxsteps} \geq 3\ell/2 + 1/2$. 

This gives $\text{maxsteps} = \Theta(\log m)$. 

Cuckoo Hashing

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

\[
\Pr[\text{unsuccessful} \mid \text{no cycle}]
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Cuckoo Hashing

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\leq \Pr[\exists \text{ active path-structure of size at least } 2^{\text{maxsteps} + 2/3}]
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We choose $\text{maxsteps} \geq 3\ell/2 + 1/2$. Then the probability that a phase terminates unsuccessfully without running into a cycle is at most

$$\Pr[\text{unsuccessful} \mid \text{no cycle}] \leq \Pr[\exists \text{ active path-structure of size at least } \frac{2\text{maxsteps}+2}{3}]$$

$$\leq \Pr[\exists \text{ active path-structure of size at least } \ell + 1]$$

$$\leq \Pr[\exists \text{ active path-structure of size exactly } \ell + 1]$$

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by choosing $\ell \geq \log \left(\frac{1}{2\mu^2m^2}\right)/\log \left(\frac{1}{1+\epsilon}\right) = \log \left(2\mu^2m^2\right)/\log \left(1 + \epsilon\right)$
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\leq \Pr[\exists \text{ active path-structure of size exactly } \ell + 1]
\leq 2\mu^2 \left( \frac{1}{1+\epsilon} \right)^\ell \leq \frac{1}{m^2}
\]

by choosing \( \ell \geq \log \left( \frac{1}{2\mu^2 m^2} \right) / \log \left( \frac{1}{1+\epsilon} \right) = \log \left( \frac{2\mu^2 m^2}{1 + \epsilon} \right) \)

This gives \( \text{maxsteps} = \Theta(\log m) \).
Cuckoo Hashing

So far we estimated

$$\Pr[\text{cycle}] \leq O\left( \frac{1}{m^2} \right)$$

and

$$\Pr[\text{unsuccessful} \mid \text{no cycle}] \leq O\left( \frac{1}{m^2} \right)$$
Cuckoo Hashing

So far we estimated

$$\Pr[\text{cycle}] \leq \mathcal{O}\left(\frac{1}{m^2}\right)$$

and

$$\Pr[\text{unsuccessful} \mid \text{no cycle}] \leq \mathcal{O}\left(\frac{1}{m^2}\right)$$

Observe that

$$\Pr[\text{successful}] = \Pr[\text{no cycle}] - \Pr[\text{unsuccessful} \mid \text{no cycle}]$$
Cuckoo Hashing

So far we estimated

\[ \Pr[\text{cycle}] \leq \Theta\left(\frac{1}{m^2}\right) \]

and

\[ \Pr[\text{unsuccessful} \mid \text{no cycle}] \leq \Theta\left(\frac{1}{m^2}\right) \]

Observe that

\[ \Pr[\text{successful}] = \Pr[\text{no cycle}] - \Pr[\text{unsuccessful} \mid \text{no cycle}] \geq c \cdot \Pr[\text{no cycle}] \]
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Observe that

$$\Pr[\text{successful}] = \Pr[\text{no cycle}] - \Pr[\text{unsuccessful} | \text{no cycle}]$$

$$\geq c \cdot \Pr[\text{no cycle}]$$

for a suitable constant $c > 0$. 
Cuckoo Hashing

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

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$$\mathbb{E}[\text{number of steps} \mid \text{phase successful}]$$
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The expected number of complete steps in the successful phase of an insert operation is:

\[ E[\text{number of steps} \mid \text{phase successful}] = \sum_{t \geq 1} \Pr[\text{search takes at least } t \text{ steps} \mid \text{phase successful}] \]
Cuckoo Hashing

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

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\]

We have

\[
\Pr[\text{search at least } t \text{ steps} \mid \text{successful}] \leq \frac{\Pr[\text{search at least } t \text{ steps} \land \text{successful}]}{\Pr[\text{no cycle}]} \leq \frac{\Pr[\text{search at least } t \text{ steps} \land \text{no cycle}]}{\Pr[\text{no cycle}]} = 1 \]

Cuckoo Hashing

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

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We have

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

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

\[ E[\text{number of steps} \mid \text{phase successful}] \]

\[ = \sum_{t \geq 1} \Pr[\text{search takes at least } t \text{ steps} \mid \text{phase successful}] \]

We have

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

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

\[ \leq \frac{1}{c} \Pr[\text{search at least } t \text{ steps } \wedge \text{ successful}] / \Pr[\text{no cycle}] \]
Cuckoo Hashing

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

\[ E[number\ of\ steps \mid phase\ successful] = \sum_{t \geq 1} Pr[search\ takes\ at\ least\ t\ steps \mid phase\ successful] \]

We have

\[ Pr[search\ at\ least\ t\ steps \mid successful] = Pr[search\ at\ least\ t\ steps \land successful]/Pr[successful] \leq \frac{1}{c} Pr[search\ at\ least\ t\ steps \land successful]/Pr[no\ cycle] \leq \frac{1}{c} Pr[search\ at\ least\ t\ steps \land no\ cycle]/Pr[no\ cycle] \]
Cuckoo Hashing

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

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

We have

\[
\Pr[\text{search at least } t \text{ steps} \mid \text{successful}] = \Pr[\text{search at least } t \text{ steps} \land \text{successful}] / \Pr[\text{successful}]
\leq \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \land \text{successful}] / \Pr[\text{no cycle}]
\leq \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \land \text{no cycle}] / \Pr[\text{no cycle}]
= \frac{1}{c} \Pr[\text{search at least } t \text{ steps} \mid \text{no cycle}].
\]
Cuckoo Hashing

Hence,

\[ E[\text{number of steps} \mid \text{phase successful}] \]
Cuckoo Hashing

Hence,

\[ E[\text{number of steps} \mid \text{phase successful}] \leq \frac{1}{c} \sum_{t \geq 1} \Pr[\text{search at least } t \text{ steps} \mid \text{no cycle}] \]
Cuckoo Hashing

Hence,

$$E[\text{number of steps | phase successful}]$$

$$\leq \frac{1}{c} \sum_{t \geq 1} \Pr[\text{search at least } t \text{ steps | no cycle}]$$

$$\leq \frac{1}{c} \sum_{t \geq 1} 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{(2t-1)/3}$$
Cuckoo Hashing

Hence,

\[ E[\text{number of steps | phase successful}] \]

\[ \leq \frac{1}{c} \sum_{t \geq 1} \Pr[\text{search at least } t \text{ steps | no cycle}] \]

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

Hence,

\[ E[\text{number of steps } | \text{ phase successful}] \]

\[ \leq \frac{1}{c} \sum_{t \geq 1} \Pr[\text{search at least } t \text{ steps } | \text{ no cycle}] \]

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

Hence,

\[ E[\text{number of steps | phase successful}] \]

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

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

A phase that is not successful induces cost for doing a complete rehash (this dominates the cost for the steps in the phase).

The probability that a phase is not successful is $p = \Theta(1/m^2)$ (probability $\Theta(1/m^2)$ of running into a cycle and probability $\Theta(1/m^2)$ of reaching maxsteps without running into a cycle).

A rehash try requires $m$ insertions and takes expected constant time per insertion. It fails with probability $p := \Theta(1/m)$.

The expected number of unsuccessful rehashes is

$$\sum_{i \geq 1} p^i = \frac{1}{1-p} - 1 = \frac{p}{1-p} = \Theta(p).$$

Therefore the expected cost for re-hashes is $\Theta(m) \cdot \Theta(p) = \Theta(1)$. 
Cuckoo Hashing

A phase that is not successful induces cost for doing a complete rehash (this dominates the cost for the steps in the phase).

The probability that a phase is not successful is $p = \mathcal{O}(1/m^2)$ (probability $\mathcal{O}(1/m^2)$ of running into a cycle and probability $\mathcal{O}(1/m^2)$ of reaching \texttt{maxsteps} without running into a cycle).

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7.7 Hashing
Cuckoo Hashing

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Therefore the expected cost for re-hashes is

$$\mathcal{O}(m) \cdot \mathcal{O}(p) = \mathcal{O}(1).$$
Cuckoo Hashing

A phase that is not successful induces cost for doing a complete rehash (this dominates the cost for the steps in the phase).

The probability that a phase is not successful is \( p = O\left(\frac{1}{m^2}\right) \) (probability \( O\left(\frac{1}{m^2}\right) \) of running into a cycle and probability \( O\left(\frac{1}{m^2}\right) \) of reaching \text{maxsteps} without running into a cycle).

A rehash try requires \( m \) insertions and takes expected constant time per insertion. It fails with probability \( p := O\left(\frac{1}{m}\right) \).

The expected number of unsuccessful rehashes is
\[
\sum_{i \geq 1} p^i = \frac{1}{1-p} - 1 = \frac{p}{1-p} = O(p).
\]

Therefore the expected cost for re-hashes is
\( O(m) \cdot O(p) = O(1) \).
Cuckoo Hashing

A phase that is not successful induces cost for doing a complete rehash (this dominates the cost for the steps in the phase).

The probability that a phase is not successful is $p = \Theta(1/m^2)$ (probability $O(1/m^2)$ of running into a cycle and probability $O(1/m^2)$ of reaching maxsteps without running into a cycle).

A rehash try requires $m$ insertions and takes expected constant time per insertion. It fails with probability $p := O(1/m)$.

The expected number of unsuccessful rehashes is

$$\sum_{i \geq 1} p^i = \frac{1}{1-p} - 1 = \frac{p}{1-p} = \Theta(p).$$

Therefore the expected cost for re-hashes is $\Theta(m) \cdot \Theta(p) = \Theta(1)$.
Cuckoo Hashing

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The probability that a phase is not successful is \( p = \Theta(1/m^2) \) (probability \( \Theta(1/m^2) \) of running into a cycle and probability \( \Theta(1/m^2) \) of reaching maxsteps without running into a cycle).

A rehash try requires \( m \) insertions and takes expected constant time per insertion. It fails with probability \( p := \Theta(1/m) \).

The expected number of unsuccessful rehashes is
\[
\sum_{i \geq 1} p^i = \frac{1}{1-p} - 1 = \frac{p}{1-p} = \Theta(p).
\]

Therefore the expected cost for re-hashes is \( \Theta(m) \cdot \Theta(p) = \Theta(1) \).
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):
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$$\Pr[Y_i] \leq (m + 1) \cdot \Theta(1/m^2) \leq \Theta(1/m) =: p.$$
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\Pr[Y_i] \leq (m + 1) \cdot O(1/m^2) \leq O(1/m) =: p .
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\Pr[Z_i] \leq \Pr[\bigwedge_{j=1}^{i-1} Y_j] \leq p^{i-1}
$$

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

$$
\mathbb{E}[X_i^s]
$$
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$$E[X_i^s] = E[\text{steps} \mid \text{phase successful}] \cdot \Pr[\text{phase successful}] + \text{maxsteps} \cdot \Pr[\text{not successful}]$$
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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):

$$E[X^s_i] = E[\text{steps | phase successful}] \cdot \Pr[\text{phase sucessful}] + \maxsteps \cdot \Pr[\text{not sucessful}] = O(1) .$$
The expected cost for all rehashes is

$$E \left[ \sum_i \sum_s Z_i X_i^s \right]$$

Note that $Z_i$ is independent of $X_i^s$, $j \geq i$ (however, it is not independent of $X_j^s$, $j < i$). Hence,
The expected cost for all rehashes is

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\[
E \left[ \sum_i \sum_s Z_i X_i^s \right] = \sum_i \sum_s E[Z_i] \cdot E[X_i^s] \\
\leq \mathcal{O}(1) \cdot \sum_i p^{i-1} \\
\leq \mathcal{O}(1) \cdot \frac{1}{1 - p} \\
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$$= \mathcal{O}(1) .$$
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.
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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.
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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 \( \frac{1}{2(1+\epsilon)} \).
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 \( \frac{1}{2(1+\epsilon)} \).