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:**

```
       6
      / \
     2   7
    / \  / \  
   1  5 8 1  2 5 6 7 8
```

```
       1
      / 
     2  5
    /  /  
   6 5  6
```

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.

- \( T. \text{insert}(x) \)
- \( T. \text{delete}(x) \)
- \( T. \text{search}(k) \)
- \( T. \text{successor}(x) \)
- \( T. \text{predecessor}(x) \)
- \( T. \text{minimum}() \)
- \( T. \text{maximum}() \)
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)
Binary Search Trees: Searching

TreeSearch(root, 17)

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, 17)

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[\(x\)], \(k\))
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, 17)

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

1: \textbf{if} \(x = \text{null or left}[x] = \text{null}\) \textbf{return} \(x\)
2: \textbf{return} TreeMin(left[\(x\)])
Binary Search Trees: Successor

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 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 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 \text{TreeSucc}(x)
\begin{align*}
1: & \hspace{1em} \text{if} \; \text{right}[x] \neq \text{null} \; \text{return} \; \text{TreeMin}(\text{right}[x]) \\
2: & \hspace{1em} y \leftarrow \text{parent}[x] \\
3: & \hspace{1em} \text{while} \; y \neq \text{null} \; \text{and} \; x = \text{right}[y] \; \text{do} \\
4: & \hspace{2em} x \leftarrow y; y \leftarrow \text{parent}[x] \\
5: & \hspace{1em} \text{return} \; y;
\end{align*}
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[$x$]
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;
**Binary Search Trees: Successor**

![Binary Search Tree Diagram]

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

1. if \( \text{right}[x] \neq \text{null} \) return \( \text{TreeMin}(\text{right}[x]) \)
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 \( x = \text{null} \) 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\( [x] = \text{null} \) then
6: left\( [x] \leftarrow z; \text{parent}[z] \leftarrow x; \)
7: else TreeInsert\( (\text{left}[x], z) \);
8: else
9: if right\( [x] = \text{null} \) then
10: right\( [x] \leftarrow z; \text{parent}[z] \leftarrow x; \)
11: else TreeInsert\( (\text{right}[x], z) \);
Binary Search Trees: Insert

Insert element **not** in the tree.

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

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:     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: Delete

```
25
  /   \
13    30
  /     /     \
 6     21     48
 /     /     /     \
3     16     26     43
 /     /     /     /     \
0     14     29     41     50
 /     /     /     /     /     \
4     17     22     47     42     55
```


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.
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
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

- 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
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
Balanced Binary Search Trees

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 \( \Theta(n) \).

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.
Balanced Binary Search Trees

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

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

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

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

similar: SPLAY trees.
Balanced Binary Search Trees

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 $\Theta(n)$.

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.
Balanced Binary Search Trees

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

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

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

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

similar: SPLAY trees.
Balanced Binary Search Trees

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

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

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

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

similar: SPLAY trees.
7.2 Red Black Trees

**Definition 1**

A red black tree is a balanced binary search tree in which each internal node has two children. Each internal node has a color, such that

1. The root is black.
2. All leaf nodes are black.
3. For each node, all paths to descendant leaves contain the same number of black nodes.
4. If a node is red then both its children are black.

The null-pointers in a binary search tree are replaced by pointers to special null-vertices, that do not carry any object-data.
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.
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.
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.
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.
Definition 1
A red black tree is a balanced binary search tree in which each internal node has two children. Each internal node has a color, such that
1. The root is black.
2. All leaf nodes are black.
3. For each node, all paths to descendant leaves contain the same number of black nodes.
4. If a node is red then both its children are black.

The null-pointers in a binary search tree are replaced by pointers to special null-vertices, that do not carry any object-data
Red Black Trees: Example

7.2 Red Black Trees
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:

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

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

Definition 3

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

We first show:

Lemma 4

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

Induction on the height of \( v \).

**Base case** (\( \text{height}(v) = 0 \))
- 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 \( 0 = 2^0 - 1 \) inner vertices.
Proof of Lemma 4.

Induction on the height of $v$.

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

1. 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.
2. The black height of $v$ is 0.
3. The sub-tree rooted at $v$ contains $0 = 2^0 - 1$ inner vertices.
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.
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.
Proof (cont.)

induction step
Suppose \( v \) is a node with height \( (v) > 0 \),
\( v \) 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
\( 2\cdot bh(v) - 1\) internal vertices.
Then \( T_v \) contains at least \( 2\cdot bh(v) - 1\) \( + 1 \) vertices.
Proof (cont.)

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

**induction step**

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

induction step

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

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

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

Hence, the black height of the root is at least $h/2$.

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

Hence, $h \leq 2 \log(n + 1) = \Theta(\log n)$. \qed
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.

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
Proof of Lemma 2.

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

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

Hence, the black height of the root is at least $h/2$.

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

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

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

RB-Insert(root, 18)

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

RB-Insert(root, 18)

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

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

**RB-Insert(root, 18)**

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

RB-Insert(root, 18)

Insert:

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

RB-Insert(root, 18)

Insert:
- first make a normal insert into a binary search tree
- then fix red-black properties
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 \( \text{parent}[z] \)
    - 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 $\text{parent}[z]$
  - 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 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 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.
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 $\text{parent}[z]$
  - 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.
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];
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
3:         uncle ← right[grandparent[\(z\)]]
4:         if col[uncle] = red then  \(\text{Case 1: uncle red}\)
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;
Red Black Trees: Insert

**Algorithm 10 InsertFix**

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 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]);
12. else same as then-clause but right and left exchanged
13. col(root[T]) ← black;
Red Black Trees: Insert

<table>
<thead>
<tr>
<th>Algorithm 10 InsertFix($z$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: while parent[$z$] $\neq$ null and col[parent[$z$]] = red do</td>
</tr>
<tr>
<td>2: if parent[$z$] = left[grandparent[$z$]] then</td>
</tr>
<tr>
<td>3:     uncle $\leftarrow$ right[grandparent[$z$]]</td>
</tr>
<tr>
<td>4: if col[uncle] = red then</td>
</tr>
<tr>
<td>5:     col[p[$z$]] $\leftarrow$ black; col[$u$] $\leftarrow$ black;</td>
</tr>
<tr>
<td>6:     col[grandparent[$z$]] $\leftarrow$ red; $z$ $\leftarrow$ grandparent[$z$];</td>
</tr>
<tr>
<td>7: else</td>
</tr>
<tr>
<td>8: if $z$ = right[parent[$z$]] then 2a: $z$ right child</td>
</tr>
<tr>
<td>9:     $z$ $\leftarrow$ p[$z$]; LeftRotate($z$);</td>
</tr>
<tr>
<td>10:    col[p[$z$]] $\leftarrow$ black; col[grandparent[$z$]] $\leftarrow$ red;</td>
</tr>
<tr>
<td>11:    RightRotate(Grandparent[$z$]);</td>
</tr>
<tr>
<td>12: else same as then-clause but right and left exchanged</td>
</tr>
<tr>
<td>13: col(root[$T$]) $\leftarrow$ black;</td>
</tr>
</tbody>
</table>
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; 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

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

1. recolor
2. move z to grand-parent
3. invariant is fulfilled for new z
4. you made progress
Case 1: Red Uncle

1. recolour
Case 1: Red Uncle

1. recolour

13

A
B
C
D
E

13

6

21

A
B
C
D
E

13

6

21

A
B
C
D
E

uncle
Case 1: Red Uncle

1. recolour
2. move $z$ to grand-parent
Case 1: Red Uncle

1. recolour
2. move $z$ to grand-parent
3. invariant is fulfilled for new $z$
Case 1: Red Uncle

1. recolour
2. move $z$ to grand-parent
3. invariant is fulfilled for new $z$
4. you made progress
Case 2b: Black uncle and $z$ is left child

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

![Red Black Tree Diagram]

7.2 Red Black Trees

Ernst Mayr, Harald Räcke
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
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
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
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
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

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

1. rotate around parent
2. move $z$ downwards
3. you have Case 2b.
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 $\Theta(\log n)$ 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.
Red Black Trees: Insert

Running time:

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

Performing Case 1 at most $\Theta(\log n)$ 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.
Red Black Trees: Insert

Running time:

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

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

First do a standard delete.

If the spliced out node $x$ was red everything is fine.

If it was black there may be the following problems.

▶ Parent and child of $x$ were red; two adjacent red vertices.
▶ If you delete the root, the root may now be red.
▶ Every path from an ancestor of $x$ to a descendant leaf of $x$ changes the number of black nodes. Black height property might be violated.
Case 3:
Element has two children
- do normal delete
- when replacing content by content of successor, don’t change color of node
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
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
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
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
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.
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.
Red Black Trees: Delete

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

- the node $z$ is black
- if we “assign” a fake black unit to the edge from $z$ to its parent then the black-height property is fulfilled

Goal: make rotations in such a way that you at some point can remove the fake black unit from the edge.
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

Invariant of the fix-up algorithm

- the node $z$ is black
- if we “assign” a fake black unit to the edge from $z$ to its parent then the black-height property is fulfilled

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

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

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

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

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

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

4. Case 2 (special), or Case 3, or Case 4
Case 1: Sibling of $z$ is red

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

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

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

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

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

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

1. re-color node \( c \)
2. move fake black unit upwards
3. move \( z \) upwards
4. we made progress
5. if \( b \) is red we color it black and are done
Case 2: Sibling is black with two black children

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

1. re-color node \( c \)
2. move fake black unit upwards
3. move z upwards
4. we made progress
5. if \( b \) is red we color it black and are done
Case 3: Sibling black with one black child to the right

1. do a right-rotation at sibling
2. recolor \( c \) and \( d \)
3. new sibling is black with red right child (Case 4)
Case 3: Sibling black with one black child to the right

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

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

1. do a right-rotation at sibling
2. recolor \(c\) and \(d\)
3. new sibling is black with red right child (Case 4)
Case 3: Sibling black with one black child to the right

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

1. left-rotate around $b$
2. remove the fake black unit
3. recolor nodes $b$, $c$, and $e$
4. you have a valid red black tree
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 → Case 2 (special) → red black tree
- Case 1 → Case 3 → Case 4 → red black tree
- Case 1 → Case 4 → red black tree
- Case 3 → Case 4 → red black tree
- Case 4 → 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.
Running time:

- only Case 2 can repeat; but only \( h \) many steps, where \( h \) is the height of the tree

- Case 1 → Case 2 (special) → red black tree
  Case 1 → Case 3 → Case 4 → red black tree
  Case 1 → Case 4 → red black tree

- Case 3 → Case 4 → red black tree

- Case 4 → 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.
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.
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.
Running time:

- only Case 2 can repeat; but only \( h \) many steps, where \( h \) is the height of the tree
- Case 1 → Case 2 (special) → red black tree
  - Case 1 → Case 3 → Case 4 → red black tree
  - Case 1 → Case 4 → red black tree
- Case 3 → Case 4 → red black tree
- Case 4 → 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.
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
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
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
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
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
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
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
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
Splay Trees

\texttt{find(}x\texttt{)}

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

**insert(x)**

- search for \( x \); \( \tilde{x} \) is last visited element during search (successor or predecessor of \( x \))
- splay(\( \tilde{x} \)) moves \( \tilde{x} \) to the root
- insert \( x \) as new root
Splay Trees

delete($x$)

- search for $x$; splay($x$); remove $x$
- search largest element $\bar{x}$ in $A$
- splay($\bar{x}$) (on subtree $A$)
- connect root of $B$ as right child of $\bar{x}$
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 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 left rotation)
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

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

7.3 Splay Trees
Splay vs. Move to Root

7.3 Splay Trees

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

[Diagram of a balanced binary tree with nodes labeled from A to H and edges indicating the splay operation from node x to the root a.]
Splay vs. Move to Root
Splay vs. Move to Root

In a splay tree, when a node is accessed, the tree is restructured to place the accessed node at the root of the tree. This process is called a splay operation. In contrast, in a move to root tree, a node is moved to the root through a sequence of rotations.

The diagram shows a splay tree with nodes labeled from A to H. The node 'x' is accessed and splayed to the top, restructuring the tree accordingly.
Splay vs. Move to Root

- Splay Trees

7.3 Splay Trees
Static Optimality

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

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

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

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

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

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

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

Conjecture:

A splay tree that only contains elements from $S$ has cost $O(\text{cost}(A, S))$, for processing $S$. 
Lemma 5

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

Introduce a potential for the data structure.

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

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

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

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.
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.

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

$$\sum_{i=1}^{k} c_i .$$
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

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

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

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 **pop** and **multipop** do not generate an underflow.

Actual cost:

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

7.3 Splay Trees
Example: Stack

Stack

- $S. \text{push}()$
- $S. \text{pop}()$
- $S. \text{multipop}(k)$: 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:

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

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

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

Amortized cost:

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

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

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

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.

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.

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

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

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

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

Hence, the amortized cost is $\hat{C}_{1 \to 0} = 1 - 1 \leq 0$. 
Example: Binary Counter

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

Amortized cost:

- Changing bit from 0 to 1:
  $$\hat{C}_{0 \to 1} = C_{0 \to 1} + \Delta \Phi = 1 + 1 \leq 2.$$

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

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

Hence, the amortized cost is $k\hat{C}_{1 \to 0} + \hat{C}_{0 \to 1} \leq 2$. 
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:**
  \[
  \hat{C}_{0 \rightarrow 1} = C_{0 \rightarrow 1} + \Delta \Phi = 1 + 1 \leq 2 .
  \]

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

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

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

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

Amortized cost:

- Changing bit from 0 to 1:
  \[ \hat{C}_{0 \rightarrow 1} = C_{0 \rightarrow 1} + \Delta\Phi = 1 + 1 \leq 2 . \]

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

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

Hence, the amortized cost is $k\hat{C}_{1 \rightarrow 0} + \hat{C}_{0 \rightarrow 1} \leq 2$. 
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:**
  \[
  \hat{C}_{0\rightarrow1} = C_{0\rightarrow1} + \Delta\Phi = 1 + 1 \leq 2 .
  \]

- **Changing bit from 1 to 0:**
  \[
  \hat{C}_{1\rightarrow0} = C_{1\rightarrow0} + \Delta\Phi = 1 - 1 \leq 0 .
  \]

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

Hence, the amortized cost is $k\hat{C}_{1\rightarrow0} + \hat{C}_{0\rightarrow1} \leq 2$.  

potential function for splay trees:

- size \( s(x) = |T_x| \)
- rank \( r(x) = \log_2(s(x)) \)
- \( \Phi(T) = \sum_{v \in T} r(v) \)

amortized cost = real cost + potential change

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

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

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

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

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

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

$\leq r'(x) - r(x)$

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

\[ \Rightarrow \text{cost}_{\text{zigzag}} \leq 3(r'(x) - r(x)) \]
Splay: Zigzag Case

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

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

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

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

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

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

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

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

Splay: Zigzag Case
Splay: Zigzag Case

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

\[
\frac{1}{2} \left( r'(p) + r'(g) - 2r'(x) \right) \\
= \frac{1}{2} \left( \log(s'(p)) + \log(s'(g)) - 2 \log(s'(x)) \right) \\
\leq \log \left( \frac{1}{2} \frac{s'(p)}{s'(x)} + \frac{1}{2} \frac{s'(g)}{s'(x)} \right) \\
\leq \log \left( \frac{1}{2} \right) = -1
\]
Amortized cost of the whole splay operation:

\[
\leq 1 + 1 + \sum_{\text{steps } t} 3(r_t(x) - r_{t-1}(x)) \\
= 2 + r(\text{root}) - r_0(x) \\
\leq \mathcal{O}(\log n)
\]
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**(ℓ): return the ℓ-th element; return “error” if the data-structure contains less than ℓ elements.

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

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

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

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...
7.4 Augmenting Data Structures

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

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

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

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

4. How does find-by-rank work?

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

**Algorithm 11 Select($x$, $i$)**

1: if $x$ = null then return error
2: if left[$x$] $\neq$ 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:

- 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 (13, 14)

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

7.4 Augmenting Data Structures

Ernst Mayr, Harald Räcke
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

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

3. How do we maintain information?

Search($k$): Nothing to do.

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

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

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

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

3. How do we maintain information?

**Search**($k$): Nothing to do.

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

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

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

\[
\begin{align*}
\text{LeftRotate}(x) & \quad |A| + |B| + |C| + 2 \\
\text{RightRotate}(z) & \quad |A| + |B| + |C| + 2 \\
\end{align*}
\]

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

Definition 7
For \(b \geq 2a - 1\) an \((a, b)\)-tree is a search tree with the following properties

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

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

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

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

Example 8

\[
\begin{array}{c}
\text{10} \\
\downarrow \\
\text{1} \quad \text{3} \quad \text{5} \\
\downarrow \\
\text{1} \quad \text{3} \\
\downarrow \\
\infty
\end{array}
\]
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

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

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 \(B^\ast\) 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

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

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).
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 $b^h$. 

7.5 $(a, b)$-trees
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 $b^h$. 

$\square$
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 $b^h$. 

□
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 $b^h$. 

\[
\square
\]
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 $b^h$. 

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

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

Search(19)

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

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

7.5 $(a, b)$-trees
Search

Search(19)

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

Time: $O(b \cdot h) = O(b \cdot \log n)$, if the individual nodes are organized as linear lists.
The search is straightforward. It is only important that you need to go all the way to the leaf.
The search is straightforward. It is only important that you need to go all the way to the leaf.

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

Insert element $x$:

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

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 $b \geq 2a - 1$.
- They get at most $\lceil \frac{b-1}{2} \rceil$ keys, and have therefore degree at most $\lfloor \frac{b-1}{2} \rfloor + 1 \leq b$ (since $b \geq 2$).
- The key $k_j$ is promoted to the parent of $v$. The current pointer to $v$ is altered to point to $v_1$, and a new pointer (to the right of $k_j$) in the parent is added to point to $v_2$.
- Then, re-balance the parent.
Insert

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 $b \geq 2a - 1$.
- They get at most $\lceil \frac{b-1}{2} \rceil$ keys, and have therefore degree at most $\lceil \frac{b-1}{2} \rceil + 1 \leq b$ (since $b \geq 2$).
- The key $k_j$ is promoted to the parent of $v$. The current pointer to $v$ is altered to point to $v_1$, and a new pointer (to the right of $k_j$) in the parent is added to point to $v_2$.
- Then, re-balance the parent.
Insert

Rebalance($v$):

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


**Insert**

**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 $b \geq 2a - 1$.
- They get at most $\lceil \frac{b-1}{2} \rceil$ keys, and have therefore degree at most $\lceil \frac{b-1}{2} \rceil + 1 \leq b$ (since $b \geq 2$).
- The key $k_j$ is promoted to the parent of $v$. The current pointer to $v$ is altered to point to $v_1$, and a new pointer (to the right of $k_j$) in the parent is added to point to $v_2$.
- Then, re-balance the parent.
**Insert**

**Rebalance**(\(\nu\)):

- Let \(k_i, i = 1, \ldots, b\) denote the keys stored in \(\nu\).
- Let \(j := \lfloor \frac{b+1}{2} \rfloor\) be the middle element.
- Create two nodes \(\nu_1\) and \(\nu_2\). \(\nu_1\) gets all keys \(k_1, \ldots, k_{j-1}\) and \(\nu_2\) 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 \(b \geq 2a - 1\).
- They get at most \(\lceil \frac{b-1}{2} \rceil\) keys, and have therefore degree at most \(\lceil \frac{b-1}{2} \rceil + 1 \leq b\) (since \(b \geq 2\)).
- The key \(k_j\) is promoted to the parent of \(\nu\). The current pointer to \(\nu\) is altered to point to \(\nu_1\), and a new pointer (to the right of \(k_j\)) in the parent is added to point to \(\nu_2\).
- Then, re-balance the parent.
Insert

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 $b \geq 2a - 1$.
- They get at most $\lceil \frac{b-1}{2} \rceil$ keys, and have therefore degree at most $\lceil \frac{b-1}{2} \rceil + 1 \leq b$ (since $b \geq 2$).
- The key $k_j$ is promoted to the parent of $v$. The current pointer to $v$ is altered to point to $v_1$, and a new pointer (to the right of $k_j$) in the parent is added to point to $v_2$.
- Then, re-balance the parent.
Insert

Rebalance($v$):

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

Insert(8)
Insert

Insert(8)

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

Insert(8)
Insert

Insert(8)
Insert

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

Insert(6)
Insert

Insert(6)
Insert

Insert(6)
Insert

Insert(6)
Insert

Insert(7)
Insert

Insert(7)
Insert

Insert(7)
Insert

Insert(7)
Insert

Insert(7)
Insert

Insert(7)
Insert

Insert(7)

\[ 7.5 \ (a, b)\text{-trees} \]
Insert

Insert(7)
Insert

Insert(7)
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’(\( v \)).
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 $\text{Rebalance}'(v)$. 
Delete

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

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

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

- 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):

- 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

Delete(10)

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

Delete(10)

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

Ernst Mayr, Harald Räcke
Delete (10)
7.5 \((a, b)\)-trees
Delete (14)
Delete

Delete(14)
Delete (14)
Delete (14)
Delete (14)
Delete(3)
Delete(3)
Delete(3)
Delete(3)
Delete

Delete(3)

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

Delete(1)

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

Delete(19)
Delete(19)
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:

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

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:

\[
\begin{align*}
&17 \\
&4 \quad 8 \\
&1 \quad 3 \\
&5 \\
&11 \quad 13 \\
&18 \quad 19 \\
&22 \\
&20 \quad 25 \quad 41 \\
&27 \\
&43 \quad 47
\end{align*}
\]
(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:

\[
\begin{array}{c}
17 \\
8 \\
4 \\
3 \\
1 \\
5 \\
13 \\
11 \\
19 \\
18 \\
20 \\
22 \\
27 \\
43 \\
41 \\
47 \\
\end{array}
\]
There is a close relation between red-black trees and \((2, 4)\)-trees:

![Diagram of red-black tree and (2, 4)-tree correspondence]
There is a close relation between red-black trees and \((2, 4)\)-trees:

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

How can we improve the search-operation?

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 $\Theta(\sqrt{n})$. 
7.6 Skip Lists

How can we improve the search-operation?

Add an express lane:
7.6 Skip Lists

How can we improve the search-operation?

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 $\Theta(\sqrt{n})$. 
How can we improve the search-operation?

**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 $\Theta(\sqrt{n})$. 
How can we improve the search-operation?

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: $|L_1| + |L_0| = O(n)$.

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

How can we improve the search-operation?

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 $\Theta(\sqrt{n})$. 
7.6 Skip Lists

How can we improve the search-operation?

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 $\Theta(\sqrt{n})$. 
7.6 Skip Lists

How can we improve the search-operation?

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: $|L_1| + |L_0| (\text{ignoring additive constants})$.

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

How can we improve the search-operation?

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 $\Theta(\sqrt{n})$. 
7.6 Skip Lists

How can we improve the search-operation?

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: $|L_1| + |L_0| = |L_1| (\text{ignoring additive constants})$

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

How can we improve the search-operation?

Add an express lane:

Let $|L_1|$ denote the number of elements in the “express lane”, and $|L_0| = n$ the number of all elements (ignoring dummy elements). Worst case search time: $|L_1| + |L_0|$ (ignoring additive constants). Choose $|L_1| = \sqrt{n}$. Then search time $\Theta(\sqrt{n})$. 
How can we improve the search-operation?

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).
How can we improve the search-operation?

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: $|L_1| + \frac{|L_0|}{|L_1|}$ (ignoring additive constants)
How can we improve the search-operation?

**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: $|L_1| + \frac{|L_0|}{|L_1|}$ (ignoring additive constants)

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

---

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

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

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

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

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

- Find the largest item in list $L_k$ that is smaller than $x$. At most $|L_k| + 2$ steps.
7.6 Skip Lists

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

Search($x$) ($k + 1$ lists $L_0, \ldots, L_k$)
- Find the largest item in list $L_k$ that is smaller than $x$. At most $|L_k| + 2$ steps.
- Find the largest item in list $L_{k-1}$ that is smaller than $x$. At most $\lceil \frac{|L_{k-1}|}{|L_k| + 1} \rceil + 2$ steps.
7.6 Skip Lists

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

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

- Find the largest item in list $L_k$ that is smaller than $x$. At most $|L_k| + 2$ steps.
- Find the largest item in list $L_{k-1}$ that is smaller than $x$. At most $\lceil \frac{|L_k|}{|L_{k-1}| + 1} \rceil + 2$ steps.
- Find the largest item in list $L_{k-2}$ that is smaller than $x$. At most $\lceil \frac{|L_k-2|}{|L_{k-1}|+1} \rceil + 2$ steps.
Add more express lanes. Lane $L_i$ contains roughly every $\frac{L_{i-1}}{L_i}$-th item from list $L_{i-1}$.

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

- Find the largest item in list $L_k$ that is smaller than $x$. At most $|L_k| + 2$ steps.
- Find the largest item in list $L_{k-1}$ that is smaller than $x$. At most $\lceil \frac{|L_{k-1}|}{|L_k|+1} \rceil + 2$ steps.
- Find the largest item in list $L_{k-2}$ that is smaller than $x$. At most $\lceil \frac{|L_{k-2}|}{|L_{k-1}|+1} \rceil + 2$ steps.
- \ldots
7.6 Skip Lists

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

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

- Find the largest item in list $L_k$ that is smaller than $x$. At most $|L_k| + 2$ steps.
- Find the largest item in list $L_{k-1}$ that is smaller than $x$. At most $\left\lceil \frac{|L_{k-1}|}{|L_k|+1} \right\rceil + 2$ steps.
- Find the largest item in list $L_{k-2}$ that is smaller than $x$. At most $\left\lceil \frac{|L_{k-2}|}{|L_{k-1}|+1} \right\rceil + 2$ steps.
- \ldots
- 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, \( L_k \approx r^{-k}n \).
7.6 Skip Lists

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: \( \mathcal{O}(r^{-k} n + kr) \).
7.6 Skip Lists

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: \( O(r^{-k}n + kr) \).

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

\[ r^{-k}n + kr \]
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:** \( O(r^{-k} n + kr) \).

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

\[
r^{-k} n + kr = \left(n^{\frac{1}{k+1}}\right)^{-k} n + kn^{\frac{1}{k+1}}
\]
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: \( O(r^{-k}n + kr) \).
Choose \( r = n^{\frac{1}{k+1}} \). Then

\[
r^{-k}n + kr = \left(n^{\frac{1}{k+1}}\right)^{-k}n + kn^{\frac{1}{k+1}}\\
= n^{1-\frac{k}{k+1}} + kn^{\frac{1}{k+1}}
\]
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: \( O(r^{-k}n + kr) \).

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

\[
r^{-k}n + kr = \left(n^{\frac{1}{k+1}}\right)^{-k}n + kn^{\frac{1}{k+1}} \\
= n^{1-k\frac{1}{k+1}} + kn^{\frac{1}{k+1}} \\
= (k + 1)n^{\frac{1}{k+1}}.
\]
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: \( O(r^{-k} n + kr) \).
Choose \( r = n^{\frac{1}{k+1}} \). Then

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

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

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.
7.6 Skip Lists

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.
7.6 Skip Lists

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.
7.6 Skip Lists

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.
7.6 Skip Lists

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.
7.6 Skip Lists

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.
7.6 Skip Lists

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.
7.6 Skip Lists

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.
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):

![Diagram of Skip List Insertion]

Ernst Mayr, Harald Räcke
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):

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

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
7.6 Skip Lists

Insert (35):
High Probability

Definition 10 (High Probability)

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

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

**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 $\alpha$. 
High Probability

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

Then the probability that all $E_i$ hold is at least

$$\Pr[E_1 \land \cdots \land E_\ell]$$
High Probability

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

Then the probability that all $E_i$ hold is at least

$$\Pr[E_1 \land \cdots \land E_\ell] = 1 - \Pr[\bar{E}_1 \lor \cdots \lor \bar{E}_\ell]$$
High Probability

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

Then the probability that all $E_i$ hold is at least

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

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

Then the probability that all $E_i$ hold is at least

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

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

Then the probability that all $E_i$ hold is at least

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

This means $\Pr[E_1 \land \cdots \land E_\ell]$ holds with high probability.
7.6 Skip Lists

**Lemma 11**

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

Backward analysis:

\[ \infty \leftrightarrow 5 \leftrightarrow 8 \leftrightarrow 10 \leftrightarrow 12 \leftrightarrow 14 \leftrightarrow 18 \leftrightarrow 23 \leftrightarrow 26 \leftrightarrow 28 \leftrightarrow 35 \leftrightarrow 43 \leftrightarrow \infty \]
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.
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.
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.
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.
Backward analysis:

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

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 \( \frac{1}{2} \). 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 $\frac{1}{2}$.

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 $\frac{1}{2}$.

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.
Backward analysis:

At each point the path goes up with probability $\frac{1}{2}$ and left with probability $\frac{1}{2}$. 
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.
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.
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.
\[
\left( \frac{n}{k} \right)^k \leq \binom{n}{k} \leq \left( \frac{en}{k} \right)^k
\]
\[
\left( \frac{n}{k} \right)^k \leq \binom{n}{k} \leq \left( \frac{en}{k} \right)^k
\]
\[
\left( \frac{n}{k} \right)^k \leq \binom{n}{k} \leq \left( \frac{en}{k} \right)^k
\]

\[
\binom{n}{k} = \frac{n!}{k! \cdot (n-k)!}
\]
\[
\left( \frac{n}{k} \right)^k \leq \binom{n}{k} \leq \left( \frac{en}{k} \right)^k
\]

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

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

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

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

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

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

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

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

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

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

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

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

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

\[
= \left( \frac{n}{k} \right)^k \cdot \frac{k^k}{k!} \leq \left( \frac{en}{k} \right)^k
\]
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.
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 $L_k$. 
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.
\[ \Pr[E_{z,k}] \]

\[ \leq (z^k)^{2^{\alpha_k} - (z - k)^{2^{\beta_k}}} \leq (2e(z^k)^{2^{\beta_k}})^{2^{\alpha_k} - \beta_k \cdot n - \gamma \alpha} \leq (2e(\beta_k + \alpha)^{2^{\beta_k}})^{2^{\alpha_k} - \alpha} \]

Choosing \( \beta = 6\alpha \) gives

\[ \leq (42\alpha)^{64\alpha} \]
Pr[$E_{z,k}$] ≤ Pr[at most $k$ heads in $z$ trials]
Pr[$E_{z,k}$] ≤ Pr[at most $k$ heads in $z$ trials] ≤ $\binom{z}{k} 2^{-(z-k)}$
Pr[$E_{z,k}$] ≤ Pr[at most $k$ heads in $z$ trials]

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

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

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

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

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

\[
\Pr[E_{z,k}] \leq \Pr[\text{at most } k \text{ heads in } z \text{ trials}]
\leq \left( \frac{z}{k} \right) 2^{-(z-k)} \leq \left( \frac{e z}{k} \right)^k 2^{-(z-k)} \leq \left( \frac{2 e z}{k} \right)^k 2^{-z}
\]

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

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

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

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

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

\[ \leq \left( \frac{2ez}{k} \right)^k 2^{-\beta k} \cdot n^{-\gamma \alpha} \leq \left( \frac{2ez}{2^{\beta} k} \right)^k \cdot n^{-\alpha} \]
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 \( z = (\beta + \alpha) \gamma \log n \)

\leq \left( \frac{2ez}{k} \right)^k 2^{-\beta k} \cdot n^{-\gamma \alpha} \leq \left( \frac{2ez}{2^\beta k} \right)^k \cdot n^{-\alpha}

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

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

\leq \left(\frac{2ez}{k}\right)^k 2^{-\beta k} \cdot n^{-\gamma \alpha} \leq \left(\frac{2ez}{2^\beta k}\right)^k \cdot n^{-\alpha}

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

now choosing \( \beta = 6\alpha \) gives
Pr[E_{z,k}] \leq \text{Pr[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 \( z = (\beta + \alpha) \gamma \log n \)

\leq \left(\frac{2ez}{k}\right)^k 2^{-\beta k} \cdot n^{-\gamma \alpha} \leq \left(\frac{2ez}{2\beta k}\right)^k \cdot n^{-\alpha}

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

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 \( z = (\beta + \alpha)\gamma \log n \)

\[
\leq \left(\frac{2ez}{k}\right)^k 2^{-\beta k} \cdot n^{-\gamma \alpha} \leq \left(\frac{2ez}{2\beta k}\right)^k \cdot n^{-\alpha}
\]

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

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

\[
\leq \left(\frac{42\alpha}{64\alpha}\right)^k n^{-\alpha} \leq n^{-\alpha}
\]
Pr[$E_{z,k}$] ≤ Pr[at most $k$ heads in $z$ trials]

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

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

\[
\leq \left(\frac{2ez}{k}\right)^{k} 2^{-\beta k} \cdot n^{-\gamma \alpha} \leq \left(\frac{2ez}{2\beta k}\right)^{k} \cdot n^{-\alpha}
\]

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

now choosing $\beta = 6\alpha$ gives

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

for $\alpha \geq 1$. 
So far we fixed $\kappa = \gamma \log n$, $\gamma \geq 1$, 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, $\Pr[\text{search requires } z \text{ steps}] \leq \Pr[E_{z,k}] + \Pr[A_{k+1}] \leq n^{\alpha-1} + n^{\gamma-1}$.

This means, the search requires at most $z$ steps, w.h.p.
So far we fixed \( k = \gamma \log n \), \( \gamma \geq 1 \), and \( z = 7\alpha \gamma \log n \), \( \alpha \geq 1 \).
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.
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
7.6 Skip Lists

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

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

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

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

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

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

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

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

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

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,

$$\Pr[\text{search requires } z \text{ steps}]$$
7.6 Skip Lists

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

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

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

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

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,

$$\Pr[\text{search requires } z \text{ steps}] \leq \Pr[E_{z,k}] + \Pr[A_{k+1}]$$
So far we fixed $k = \gamma \log n$, $\gamma \geq 1$, and $z = 7\alpha \gamma \log n$, $\alpha \geq 1$.

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

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

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

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,

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

$$\leq n^{-\alpha} + n^{-(\gamma-1)}$$
7.6 Skip Lists

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

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

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

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

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.
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.
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.
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 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.
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 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.
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 $h : U \rightarrow [0,\ldots,n-1]$.

The hash-function $h$ should fulfill:

- Fast to evaluate.
- Small storage requirement.
- Good distribution of elements over the whole table.
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 $h : U \rightarrow [0, \ldots, n−1]$.

The hash-function $h$ should fulfill:

- Fast to evaluate.
- Small storage requirement.
- Good distribution of elements over the whole table.
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 $h : U \rightarrow [0,\ldots,n-1]$.

The hash-function $h$ should fulfill:

- Fast to evaluate.
- Small storage requirement.
- Good distribution of elements over the whole table.
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 $h : U \rightarrow [0, \ldots, n-1]$.

The hash-function $h$ should fulfill:

- Fast to evaluate.
- Small storage requirement.
- Good distribution of elements over the whole table.
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 $h: U \rightarrow [0, \ldots, n - 1]$.

The hash-function $h$ should fulfill:

- Fast to evaluate.
- Small storage requirement.
- Good distribution of elements over the whole table.
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.
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 $h : U \rightarrow [0,\ldots,n-1]$.

The hash-function $h$ should fulfill:

- Fast to evaluate.
- Small storage requirement.
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 $h : U \rightarrow [0, \ldots, n - 1]$.

The hash-function $h$ should fulfill:

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

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

Lemma 12
The probability of having a collision when hashing $m$ elements into a table of size $n$ under uniform hashing is at least

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

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

7.7 Hashing
Collisions

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

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

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

**Lemma 12**

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

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

**Uniform hashing:**

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

7.7 Hashing

Ernst Mayr, Harald Räcke

11. Apr. 2018

224/301
Collisions

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

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

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

\[
\Pr[A_{m,n}]
\]

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

Proof.

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

$$\Pr[A_{m,n}] = \prod_{\ell=1}^{m} \frac{n - \ell + 1}{n}$$
Collisions

Proof.

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

$$\Pr[A_{m,n}] = \prod_{\ell=1}^{m} \frac{n - \ell + 1}{n} = \prod_{j=0}^{m-1} \left(1 - \frac{j}{n}\right)$$
Collisions

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

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

$$\leq \prod_{j=0}^{m-1} e^{-j/n}$$
Collisions

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

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

$$\leq \prod_{j=0}^{m-1} e^{-j/n} = e^{-\sum_{j=0}^{m-1} \frac{j}{n}}$$
Collisions

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

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

$$\leq \prod_{j=0}^{m-1} e^{-j/n} = e^{-\sum_{j=0}^{m-1} \frac{j}{n}} = e^{-\frac{m(m-1)}{2n}}.$$
Collisions

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

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

$$\leq \prod_{j=0}^{m-1} e^{-j/n} = e^{-\sum_{j=0}^{m-1} \frac{j}{n}} = e^{-\frac{m(m-1)}{2n}}.$$ 

Here the first equality follows since the $\ell$-th element that is hashed has a probability of $\frac{n - \ell + 1}{n}$ to not generate a collision under the condition that the previous elements did not induce collisions. □
The inequality $1 - x \leq e^{-x}$ is derived by stopping the Taylor-expansion of $e^{-x}$ after the second term.
Resolving Collisions

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

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

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

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

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

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

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

The time required for an unsuccessful search is 1 plus the length of the list that is examined.
Hashing with Chaining

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 \( \alpha = \frac{m}{n} \).
Hashing with Chaining

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

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

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

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

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

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

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

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

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

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

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

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

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

\[
= 1 + \frac{1}{mn} \sum_{i=1}^{m} (m - i)
\]

Hence, the expected cost for a successful search is

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

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

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

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

\[
= 1 + \frac{1}{mn} \sum_{i=1}^{m} (m - i)
\]

\[
= 1 + \frac{1}{mn} \left(m^2 - \frac{m(m + 1)}{2}\right)
\]

\[
= 1 + \frac{m - 1}{2n}
\]

Hence, the expected cost for a successful search is

\[\leq 1 + \frac{m - 1}{2n}\]
Hashing with Chaining

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

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

\[
= 1 + \frac{1}{mn} \sum_{i=1}^{m} (m - i)
\]

\[
= 1 + \frac{1}{mn} \left( m^2 - \frac{m(m + 1)}{2} \right)
\]

\[
= 1 + \frac{m - 1}{2n} = 1 + \frac{\alpha}{2} - \frac{\alpha}{2m}.
\]

Hence, the expected cost for a successful search is

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

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

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

\[
= 1 + \frac{1}{mn} \sum_{i=1}^{m} (m - i)
\]

\[
= 1 + \frac{1}{mn} \left( m^2 - \frac{m(m + 1)}{2} \right)
\]

\[
= 1 + \frac{m - 1}{2n} = 1 + \frac{\alpha}{2} - \frac{\alpha}{2m}.
\]

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

All objects are stored in the table itself.

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

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

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

All objects are stored in the table itself.

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

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

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

All objects are stored in the table itself.

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

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

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

All objects are stored in the table itself.

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

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

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

Choices for $h(k, j)$:

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

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

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

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

Choices for $h(k, j)$:

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

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

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

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

Choices for $h(k, j)$:

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

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

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

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

Choices for $h(k, j)$:

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

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

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

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

▶ Advantage: **Cache-efficiency**. The new probe position is very likely to be in the cache.

▶ Disadvantage: **Primary clustering**. Long sequences of occupied table-positions get longer as they have a larger probability to be hit. Furthermore, they can merge forming larger sequences.

**Lemma 13**

Let \( L \) be the method of linear probing for resolving collisions:

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

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

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

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

**Lemma 14**

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

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

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

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

Lemma 15
Let $A$ be the method of double hashing for resolving collisions:

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

\[
D^- \approx \frac{1}{1 - \alpha}
\]
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></th>
<th><strong>Quadratic Probing</strong></th>
<th></th>
<th><strong>Double Hashing</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$L^+$</td>
<td>$L^-$</td>
<td>$Q^+$</td>
<td>$Q^-$</td>
<td>$D^+$</td>
</tr>
<tr>
<td>0.5</td>
<td>1.5</td>
<td>2.5</td>
<td>1.44</td>
<td>2.19</td>
<td>1.39</td>
</tr>
<tr>
<td>0.9</td>
<td>5.5</td>
<td>50.5</td>
<td>2.85</td>
<td>11.40</td>
<td>2.55</td>
</tr>
<tr>
<td>0.95</td>
<td>10.5</td>
<td>200.5</td>
<td>3.52</td>
<td>22.05</td>
<td>3.15</td>
</tr>
</tbody>
</table>
Open Addressing

#probes

\[ \alpha \]

\[ \#\text{probes} \]

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

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

\[ \alpha \]

7.7 Hashing
Analysis of Idealized Open Address Hashing

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

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

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

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

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

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

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

$$\Pr[X \geq i]$$
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.

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

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

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.

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

$$
\Pr[X \geq i] = \frac{m}{n} \cdot \frac{m-1}{n-1} \cdot \frac{m-2}{n-2} \cdot \ldots \cdot \frac{m-i+2}{n-i+2}
$$

$$
\leq \left(\frac{m}{n}\right)^{i-1}
$$
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.

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

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

\[ E[X] \]
Analysis of Idealized Open Address Hashing

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

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

\[ E[X] = \sum_{i=1}^{\infty} \Pr[X \geq i] \leq \sum_{i=1}^{\infty} \alpha^{i-1} = \sum_{i=0}^{\infty} \alpha^i \]
Analysis of Idealized Open Address Hashing

\[ E[X] = \sum_{i=1}^{\infty} \Pr[X \geq i] \leq \sum_{i=1}^{\infty} \alpha^{i-1} = \sum_{i=0}^{\infty} \alpha^i = \frac{1}{1 - \alpha}. \]
Analysis of Idealized Open Address Hashing

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

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

\[ i = 1 \]

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

\[ i = 2 \]

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

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

\( i = 3 \)

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

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 \( i = 1, 2, \ldots, j \)).
$i = 4$

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

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

\[ i = 1 \]

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

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

\[ i = 2 \]

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

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

\( i = 3 \)

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

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

\[ i = 4 \]

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

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 \( i = 1, 2, \ldots, j \)).
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 \( i = 1, 2, ..., j \)).
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 \( \frac{1}{1 - \frac{i}{n}} = \frac{n}{n - i} \).

\[
\sum_{i=0}^{m} \int_{n-m+1}^{n} x \, dx = \alpha \ln \frac{n}{n-m} = \alpha \ln 1 - \alpha .
\]
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.
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 $\frac{1}{1-i/n} = \frac{n}{n-i}$.
The number of probes in a successful search for $k$ is equal to the number of probes made in an unsuccessful search for $k$ at the time that $k$ is inserted.

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

\[
\frac{1}{m} \sum_{i=0}^{m-1} \frac{n}{n-i}
\]
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 $\frac{1}{1-i/n} = \frac{n}{n-i}$.

\[
\frac{1}{m} \sum_{i=0}^{m-1} \frac{n}{n-i} = \frac{n}{m} \sum_{i=0}^{m-1} \frac{1}{n-i}
\]
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 \( \frac{1}{1-i/n} = \frac{n}{n-i} \).

\[
\frac{1}{m} \sum_{i=0}^{m-1} \frac{n}{n-i} = \frac{n}{m} \sum_{i=0}^{m-1} \frac{1}{n-i} = \frac{1}{\alpha} \sum_{k=n-m+1}^{n} \frac{1}{k}
\]
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 \( \frac{1}{1-i/n} = \frac{n}{n-i} \).

\[
\frac{1}{m} \sum_{i=0}^{m-1} \frac{n}{n-i} = \frac{n}{m} \sum_{i=0}^{m-1} \frac{1}{n-i} = \frac{1}{\alpha} \sum_{k=n-m+1}^{n} \frac{1}{k}
\]

\[
\leq \frac{1}{\alpha} \int_{n-m}^{n} \frac{1}{x} \, dx
\]
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 \( \frac{1}{1-i/n} = \frac{n}{n-i} \).

\[
\frac{1}{m} \sum_{i=0}^{m-1} \frac{n}{n-i} = \frac{n}{m} \sum_{i=0}^{m-1} \frac{1}{n-i} = \frac{1}{\alpha} \sum_{k=n-m+1}^{n} \frac{1}{k} \\
\leq \frac{1}{\alpha} \int_{n-m}^{n} \frac{1}{x} \, dx = \frac{1}{\alpha} \ln \frac{n}{n-m}
\]
The number of probes in a successful search for $k$ is equal to the number of probes made in an unsuccessful search for $k$ at the time that $k$ is inserted.

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

\[
\frac{1}{m} \sum_{i=0}^{m-1} \frac{n}{n-i} = \frac{n}{m} \sum_{i=0}^{m-1} \frac{1}{n-i} = \frac{1}{\alpha} \sum_{k=n-m+1}^{n} \frac{1}{k}
\]

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

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

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

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

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

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

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

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

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

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

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

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

Algorithm 12 delete($p$)

1: $T[p] \leftarrow$ null
2: $p \leftarrow$ succ($p$)
3: while $T[p] \neq$ null do
4: $y \leftarrow T[p]$
5: $T[p] \leftarrow$ null
6: $p \leftarrow$ succ($p$)
7: insert($y$)

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

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

Pointers into the hash-table become invalid.
Universal Hashing

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Definition 16
A class $\mathcal{H}$ of hash-functions from the universe $U$ into the set $\{0, \ldots, n - 1\}$ is called universal if for all $u_1, u_2 \in U$ with $u_1 \neq u_2$

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

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

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

Definition 16
A class $\mathcal{H}$ of hash-functions from the universe $U$ into the set \{0,\ldots,n-1\} is called universal if for all \(u_1, u_2 \in U\) with \(u_1 \neq u_2\)

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

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

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

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**

**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 $\mathcal{H}$. 
Universal Hashing

**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 $\mathcal{H}$. 
Universal Hashing

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

$$\mathcal{H} = \{h_{a,b} | a \in \mathbb{Z}_p^*, b \in \mathbb{Z}_p\}$$

is a universal class of hash-functions from $U$ to $\{0, \ldots, n - 1\}$. 
Universal Hashing

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 $\{0, \ldots, n - 1\}$. 
Universal Hashing

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 \( \{0, \ldots, n - 1\} \).
Universal Hashing

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

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 $x \neq y \pmod{p}$.

Multiplying with $a \neq 0 \pmod{p}$ gives $a(x - y) \neq 0 \pmod{p}$, 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 \( 1/n \).

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

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

Multiplying with \( a \not\equiv 0 \pmod{p} \) gives

\[ ax - ay \not\equiv 0 \pmod{p} \]

where we use that \( \mathbb{Z}/p \mathbb{Z} \) 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 \( 1/n \).

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

If \( x \neq y \) then \( x - y \neq 0 \pmod{p} \).

Multiplying with \( a \neq 0 \pmod{p} \) gives

\[ a(x - y) \neq 0 \pmod{p} \]

where we use that \( \mathbb{Z}_p \) is a field (Körper) and, hence, has no zero divisors (nullteilerfrei).
Proof.
Let $x, y \in U$ be two distinct keys. We have to show that the probability of a collision is only $1/n$.

- $ax + b \not\equiv ay + b \pmod{p}$

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

Multiplying with $a \not\equiv 0 \pmod{p}$ gives

$$a(x - y) \not\equiv 0 \pmod{p}$$

where we use that $\mathbb{Z}_p$ is a field (Körper) and, hence, has no zero divisors (nullteilerfrei).
Proof.
Let $x, y \in U$ be two distinct keys. We have to show that the probability of a collision is only $1/n$. 

Let $ax + b \not\equiv ay + b \pmod{p}$. 

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

Multiplying with $a \not\equiv 0 \pmod{p}$ gives 

$$a(x - y) \not\equiv 0 \pmod{p}$$

where we use that $\mathbb{Z}_p$ is a field (Körper) and, hence, has no zero divisors (nullteilerfrei).
Universal Hashing

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

- \( ax + b \not\equiv ay + b \pmod{p} \)

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

Multiplying with \( a \not\equiv 0 \pmod{p} \) gives

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

where we use that \( \mathbb{Z}_p \) is a field (Körper) and, hence, has no zero divisors (nullteilerfrei).
Universal Hashing

- The hash-function does not generate collisions before the \((\mod n)\)-operation. Furthermore, every choice \((a, b)\) is mapped to a different pair \((t_x, t_y)\) with \(t_x := ax + b\) and \(t_y := ay + b\).
Universal Hashing

- The hash-function does not generate collisions before the \((\mod n)\)-operation. Furthermore, every choice \((a, b)\) is mapped to a different pair \((t_x, t_y)\) with \(t_x := ax + b\) and \(t_y := ay + b\).

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

The hash-function does not generate collisions before the \((\mod n)\)-operation. Furthermore, every choice \((a, b)\) is mapped to a different pair \((tx, ty)\) with \(tx := ax + b\) and \(ty := ay + b\).

This holds because we can compute \(a\) and \(b\) when given \(tx\) and \(ty\):

\[
\begin{align*}
    tx & \equiv ax + b \quad \pmod{p} \\
    ty & \equiv ay + b \quad \pmod{p}
\end{align*}
\]
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 \(t_y := ay + b\).

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

\[
\begin{align*}
t_x &\equiv ax + b \pmod{p} \\
t_y &\equiv ay + b \pmod{p}
\end{align*}
\]

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

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

\[
\begin{align*}
t_x & \equiv ax + b \pmod{p} \\
t_y & \equiv ay + b \pmod{p} \\
t_x - t_y & \equiv a(x - y) \pmod{p} \\
t_y & \equiv ay + b \pmod{p} \\
a & \equiv (t_x - t_y)(x - y)^{-1} \pmod{p} \\
b & \equiv t_y - ay \pmod{p}
\end{align*}
\]
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 \(\lceil p/n \rceil\) values.
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\text{-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\text{ operation}?

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

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

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

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

As $t_y \neq t_x$ there are

$$\left\lceil p^n \right\rceil - 1 \leq p^n + n - 1 \leq p - 1$$

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

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

As $t_y \neq t_x$ there are

$$\left\lceil \frac{p}{n} \right\rceil - 1 \leq \frac{p}{n} + \frac{n-1}{n} - 1 \leq \frac{p-1}{n}$$

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

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

As \( t_y \neq t_x \) there are

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

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

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

As $t_y \neq t_x$ there are

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

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

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

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

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

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

As $t_Y \neq t_X$ there are

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

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

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

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

$$\Pr[t_x \neq t_y \in \mathbb{Z}_p \mid t_x \mod n = h_1 \land t_y \mod n = h_2] \leq \frac{p(p-1)}{\lceil \frac{p}{n} \rceil}$$

Note that the middle is the probability that $h(x)$ and $h(y)$.

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 $\lfloor \frac{p}{n} \rfloor$ and $\lceil \frac{p}{n} \rceil$. 
Universal Hashing

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

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

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

\[
\frac{\left\lfloor \frac{p}{n} \right\rfloor^2}{p(p-1)} \leq \Pr_{t_x \neq t_y \in \mathbb{Z}_n^p} \left[ \begin{array}{c}
\land \quad t_x \mod n = h_1 \\
\land \quad t_y \mod n = h_2
\end{array} \right] \leq \frac{\left\lceil \frac{p}{n} \right\rceil^2}{p(p-1)}
\]
Universal Hashing

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

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

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 $\left\lceil \frac{p}{n} \right\rceil$. 
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 $\mathcal{H}^d_n := \{h_{\bar{a}} \mid \bar{a} \in \{0, \ldots, q - 1\}^{d+1}\}$. The class $\mathcal{H}^d_n$ is $(e, d + 1)$-independent.

Note that in the previous case we had $d = 1$ and chose $a_d \neq 0$. 
For the coefficients $\vec{a} \in \{0, \ldots, q - 1\}^{d+1}$ let $f_{\vec{a}}$ denote the polynomial

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

The polynomial is defined by $d + 1$ distinct points.
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.
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.
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
\[
h_\bar{a} \in A^\ell \iff h_\bar{a} = f_\bar{a} \mod n \text{ and } f_\bar{a}(x_i) \in \{t_i + \alpha \cdot n \mid \alpha \in \{0, \ldots, \lceil \frac{q}{n} \rceil - 1\}\}
\]

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.

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

\[
h_\bar{a} \in A^\ell \iff h_\bar{a} = f_\bar{a} \mod n \text{ and } f_\bar{a}(x_i) \in \{t_i + \alpha \cdot n \mid \alpha \in \{0, \ldots, \lceil \frac{q}{n} \rceil - 1\}\}
\]

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.

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

Then $h_\alpha \in A^\ell \iff h_\alpha = f_\alpha \mod n$ and

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

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

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

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

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.

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

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

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

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.

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

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

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

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.

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

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

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

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

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

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

possibilities to choose $\bar{a}$ such that $h\bar{a} \in A_\ell$. 
Therefore the probability of choosing $h_{\bar{a}}$ from $A_\ell$ is only

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

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

$$\frac{\left\lfloor \frac{q}{n} \right\rfloor \cdot q^{d-\ell+1}}{q^{d+1}} \leq \frac{(\frac{q+n}{n})^\ell}{q^\ell} \leq \left(\frac{q+n}{q}\right)^\ell \cdot \frac{1}{n^\ell}$$
Universal Hashing

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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 $\frac{1}{2}$. 

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 $\frac{1}{2}$.
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 $\frac{1}{2}$. 
Perfect Hashing

Let $m = \lvert S \rvert$. 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 $\frac{1}{2}$.  

Ernst Mayr, Harald Räcke

7.7 Hashing
Perfect Hashing

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$U$ universe of keys

$S$ (actual keys)

$k_1, k_2, k_3, k_4, k_5, k_6, k_7, k_8$

$\emptyset, m_2, m_3, \emptyset, \emptyset, m_6, \emptyset, m_8$

$\sum_i m_i = m$

$k_1$ $k_6$ $\emptyset$ $k_4$ $\emptyset$

$m_2^2$ $m_3^2$

$\emptyset$ $\emptyset$ $k_3$ $k_2$

$m_6^2$

$\emptyset$ $\emptyset$ $\emptyset$ $k_8$ $k_5$ $\emptyset$ $\emptyset$ $k_7$ $\emptyset$

$m_8^2$
The total memory that is required by all hash-tables is $O\left(\sum j \cdot m^2 j\right)$. Note that $m^2 j$ is a random variable.

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

The first expectation is simply the expected number of collisions, for the first level. Since we use universal hashing we have $E\left[\sum j \cdot (m^2 j)\right] = 2(m - 1)$. 

7.7 Hashing 11. Apr. 2018
Ernst Mayr, Harald Räcke
Perfect Hashing

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

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

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

$$E\left[\sum_j m_j^2\right] = E\left[2 \sum_j \left(\frac{m_j}{2}\right) + \sum_j m_j\right]$$
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 $\Theta(\sum_j m_j^2)$. Note that $m_j$ is a random variable.

\[
E\left[ \sum_j m_j^2 \right] = E\left[ 2 \sum_j \binom{m_j}{2} + \sum_j m_j \right]
\]

\[
= 2 E\left[ \sum_j \binom{m_j}{2} \right] + E\left[ \sum_j m_j \right]
\]

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

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

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

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

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

$$= 2 \binom{m}{2} \frac{1}{m} + m = 2m - 1 .$$
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.
Cuckoo Hashing

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

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

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

- Two hash-tables $T_1[0,\ldots,n-1]$ and $T_2[0,\ldots,n-1]$, with hash-functions $h_1$, and $h_2$.
- An object $x$ is either stored at location $T_1[h_1(x)]$ or $T_2[h_2(x)]$.
- A search clearly takes constant time if the above constraint is met.
Goal:
Try to generate a hash-table with constant worst-case search time in a dynamic scenario.

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

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

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

Insert:

$T_1$

$T_2$
Cuckoo Hashing

Insert:

\[
\begin{align*}
T_1 & : \\
& \emptyset \\
& \emptyset \\
& \emptyset \\
& x_4 \\
& x_1 \\
& \emptyset \\
& \emptyset \\
T_2 & : \\
& \emptyset \\
& \emptyset \\
& \emptyset \\
& x_9 \\
& \emptyset \\
& \emptyset \\
& \emptyset \\
\end{align*}
\]
Cuckoo Hashing

Insert:

$x$

$T_1$

$T_2$

$7.7$ Hashing

Ernst Mayr, Harald Räcke
Cuckoo Hashing

Insert:

\[
\begin{array}{c}
\emptyset \\
\emptyset \\
\emptyset \\
x_4 \\
x_1 \\
\emptyset \\
\emptyset \\
\emptyset \\
\emptyset
\end{array}
\] \quad \rightarrow \quad
\begin{array}{c}
\emptyset \\
\emptyset \\
\emptyset \\
x_9 \\
x_3 \\
\emptyset \\
\emptyset \\
\emptyset \\
\emptyset
\end{array}

x \quad \rightarrow \quad
\begin{array}{c}
x \\
\emptyset \\
\emptyset \\
x_4 \\
x_1 \\
\emptyset \\
\emptyset \\
\emptyset \\
\emptyset
\end{array}
\quad \rightarrow \quad
\begin{array}{c}
\emptyset \\
\emptyset \\
\emptyset \\
x_9 \\
x_3 \\
\emptyset \\
\emptyset \\
\emptyset \\
\emptyset
\end{array}

x_7 

x_6 

x_7
Cuckoo Hashing

Insert:

\[
\begin{align*}
\emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad x_1 & \quad x_4 & \quad x_6 & \quad T_1 \\
\emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad x & \quad x_7 & \quad \emptyset & \quad \emptyset & \quad T_2 \\
\emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset & \quad \emptyset
\end{align*}
\]
Cuckoo Hashing

**Algorithm 13 Cuckoo-Insert($x$)**

1. if $T_1[h_1(x)] = x$ or $T_2[h_2(x)] = x$ 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 $x = \text{null}$. 
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.
- 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

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?
Cuckoo Hashing

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?
Cuckoo Hashing

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?
Cuckoo Hashing

What is the expected time for an insert-operation?

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

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

\[ T_1 \]

\[ T_2 \]
Cuckoo Hashing: Insert
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ x_2 \]

\[ T_2 \]
Cuckoo Hashing: Insert

$x = x_1 

x_1 \rightarrow x_2 \rightarrow x_2 \rightarrow x_3 \rightarrow x_3 

T_1 \rightarrow T_2$
Cuckoo Hashing: Insert

\[
x = x_1 \quad x_1 \quad x_2 \quad x_2 \\
x_3 \quad x_3 \\
T_1 \quad x_4 \\
T_2
\]
Cuckoo Hashing: Insert

\[ \begin{align*}
T_1 & : x = x_1, \\
T_2 & : x_2, x_3, x_4, \quad x_5
\end{align*} \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ x_1 \]

\[ x_3 \]

\[ x_5 \]

\[ T_2 \]

\[ x_2 \]

\[ x_3 \]

\[ x_4 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ x_1 \]

\[ x_3 \]

\[ x_5 \]

\[ T_2 \]

\[ x_2 \]

\[ x_4 \]

\[ x_6 \]

\[ x_7 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ x_1 \]
\[ x_3 \]
\[ x_5 \]
\[ x_7 \]

\[ x_2 \]
\[ x_3 \]
\[ x_5 \]
\[ x_7 \]

\[ x_4 \]
\[ x_6 \]

\[ T_2 \]

\[ x_8 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ T_2 \]

\[ x = x_1 \]

\[ x_1 \]

\[ x_2 \]

\[ x_3 \]

\[ x_4 \]

\[ x_5 \]

\[ x_6 \]

\[ x_7 \]

\[ x_8 \]

\[ x_4 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ x = x_1 \]

\[ x_2 \]

\[ x_3 \]

\[ x_4 \]

\[ x_5 \]

\[ x_6 \]

\[ x_7 \]

\[ x_8 \]

\[ T_1 \]

\[ x_3 \]

\[ T_2 \]
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ x_1 \]

\[ x_2 \]

\[ T_1 \]

\[ x_3 \]

\[ x_4 \]

\[ x_5 \]

\[ x_6 \]

\[ x_7 \]

\[ T_2 \]

\[ x_8 \]
Cuckoo Hashing: Insert
Cuckoo Hashing: Insert

\[ x = x_1 \]

\[ T_1 \]

\[ x_2 \]
\[ x_4 \]
\[ x_5 \]
\[ x_7 \]

\[ T_2 \]

\[ x \]
\[ x_2 \]
\[ x_3 \]
\[ x_4 \]
\[ x_8 \]
\[ x_6 \]

\[ x = x_1 \]

\[ x_3 \]
\[ x_5 \]
\[ x_6 \]
\[ x_8 \]

\[ x_7 \]
\[ x_9 \]
Cuckoo Hashing: Insert

7.7 Hashing

Ernst Mayr, Harald Räcke
Cuckoo Hashing: Insert
Cuckoo Hashing: Insert
Cuckoo Hashing: Insert
Cuckoo Hashing: Insert

\[ x = x_1, x_5, x_6, x_7, x_8 = x_4 \]

\[ T_1, T_2 \]
A **cycle-structure of size** $s$ is defined by

- $s - 1$ different cells (alternating blue cells from $T_1$ and $T_2$).
- $s$ distinct keys $x = x_1, x_2, ..., x_s$, 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.
A cycle-structure of size $s$ is defined by

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

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

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

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

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

- $s - 1$ different cells (alternating btw. cells from $T_1$ and $T_2$).
- $s$ distinct keys $x = x_1, x_2, \ldots, x_s$, linking the cells.
- The leftmost cell is “linked forward” to some cell on the right.
- The rightmost cell is “linked backward” to a cell on the left.
- One link represents key $x$; this is where the counting starts.
A cycle-structure is **active** if for every key $x_\ell$ (linking a cell $p_i$ from $T_1$ and a cell $p_j$ from $T_2$) we have

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

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

A cycle-structure 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 $s \geq 3$. 
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

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.

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 $\frac{\mu}{ns}$ since $h_2$ is a $(\mu, s)$-independent hash-function.

These events are independent.
Cuckoo Hashing

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

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

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

These events are independent.
Cuckoo Hashing

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.

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 $\frac{\mu}{ns}$ since $h_2$ is a $(\mu, s)$-independent hash-function.

These events are independent.
Cuckoo Hashing

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

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

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

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

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

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

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

The number of cycle-structures of size $s$ is at most

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

$$s^3 \cdot n^{s-1} \cdot m^{s-1}.$$ 

- There are at most $s^2$ possibilities where to attach the forward and backward links.
- There are at most $s$ possibilities to choose where to place key $x$.
- There are $m^{s-1}$ possibilities to choose the keys apart from $x$.
- There are $n^{s-1}$ possibilities to choose the cells.
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 $x$.
- There are $n^{s-1}$ possibilities to choose the cells.
The number of cycle-structures of size \( s \) is at most

\[
s^3 \cdot n^{s-1} \cdot m^{s-1}.
\]

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

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

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

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

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

\[
\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} = \frac{\mu^2}{nm} \sum_{s=3}^{\infty} s^3 \left( \frac{m}{n} \right)^s
\]

\[
\leq \frac{\mu^2}{m^2} \sum_{s=3}^{\infty} s^3 \left( \frac{1}{1 + \epsilon} \right)^s \leq O \left( \frac{1}{m^2} \right)
\]
The probability that there exists an active cycle-structure is therefore at most

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

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

\[
\sum_{s=3}^{\infty} s^3 \cdot n^{s-1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} = \frac{\mu^2}{nm} \sum_{s=3}^{\infty} s^3 \left( \frac{m}{n} \right)^s
\]

\[
\leq \frac{\mu^2}{m^2} \sum_{s=3}^{\infty} s^3 \left( \frac{1}{1 + \epsilon} \right)^s \leq \Theta \left( \frac{1}{m^2} \right).
\]

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

Hence,

\[
\Pr[\text{cycle}] = \Theta \left( \frac{1}{m^2} \right).
\]
Cuckoo Hashing

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 $\mathbf{x}$ 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 $\mathbf{x}$ of distinct keys.
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.*
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:

$$x = x_1 \to x_2 \to \cdots \to x_i \to x_r \to x_{r-1} \to \cdots \to x_1 \to x_{i+1} \to \cdots \to x_j$$

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

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

Either sub-sequence $x_1 \to x_2 \to \cdots \to x_i$ or sub-sequence $x_1 \to x_{i+1} \to \cdots \to x_j$ has at least \( \frac{p+2}{3} \) elements.
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. \(\square\)
A path-structure of size $s$ is defined by

- $s + 1$ different cells (alternating btw. cells from $T_1$ and $T_2$).
- $s$ distinct keys $x_1, x_2, ..., x_s$, linking the cells.
- The leftmost cell is either from $T_1$ or $T_2$. 

Cuckoo Hashing
A path-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 either from $T_1$ or $T_2$.  

Cuckoo Hashing
Cuckoo Hashing

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

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

**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

$$2 \cdot n^{s+1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}}$$
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

$$2 \cdot n^{s+1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}}$$

$$\leq 2\mu^2 \left(\frac{m}{n}\right)^{s-1}$$
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

$$2 \cdot n^{s+1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}}$$

$$\leq 2\mu^2 \left( \frac{m}{n} \right)^{s-1} \leq 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{s-1}$$
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

\[
2 \cdot n^{s+1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}}
\leq 2\mu^2 \left( \frac{m}{n} \right)^{s-1} \leq 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{s-1}
\]

Plugging in \( s = (2t + 2)/3 \) gives
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

$2 \cdot n^{s+1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}}$

$\leq 2\mu^2 \left( \frac{m}{n} \right)^{s-1} \leq 2\mu^2 \left( \frac{1}{1+\epsilon} \right)^{s-1}$

Plugging in $s = (2t + 2)/3$ gives

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

$$2 \cdot n^{s+1} \cdot m^{s-1} \cdot \frac{\mu^2}{n^{2s}} \leq 2\mu^2 \left( \frac{m}{n} \right)^{s-1} \leq 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{s-1}$$

Plugging in $s = \frac{(2t + 2)}{3}$ gives

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

We choose $\text{maxsteps} \geq 3\ell/2 + 1/2$. 
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

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

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

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

$$\Pr[\text{unsuccessful} \mid \text{no cycle}]$$

$$\leq \Pr[\exists \text{ active path-structure of size at least } \frac{2\text{maxsteps}+2}{3}]$$

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

\[
\Pr[\text{unsuccessful} \mid \text{no cycle}] \\
\leq \Pr[\exists \text{ active path-structure of size at least } \frac{2\text{maxsteps} + 2}{3}] \\
\leq \Pr[\exists \text{ active path-structure of size at least } \ell + 1] \\
\leq \Pr[\exists \text{ active path-structure of size exactly } \ell + 1]
\]
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

\[
\Pr[\text{unsuccessful} \mid \text{no cycle}]
\leq \Pr[\exists \text{ active path-structure of size at least } \frac{2\text{maxsteps}+2}{3}]
\leq \Pr[\exists \text{ active path-structure of size at least } \ell + 1]
\leq \Pr[\exists \text{ active path-structure of size exactly } \ell + 1]
\leq 2\mu^2\left(\frac{1}{1 + \epsilon}\right)\ell
\]

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

\[
\Pr[\text{unsuccessful} \mid \text{no cycle}] \\
\leq \Pr[\exists \text{ active path-structure of size at least } \frac{2\text{maxsteps}+2}{3}] \\
\leq \Pr[\exists \text{ active path-structure of size at least } \ell + 1] \\
\leq \Pr[\exists \text{ active path-structure of size exactly } \ell + 1] \\
\leq 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)\ell \leq \frac{1}{m^2}
\]
Cuckoo Hashing

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

$$\Pr[\text{unsuccessful} \mid \text{no cycle}]$$

$$\leq \Pr[\exists \text{ active path-structure of size at least } \frac{2\maxsteps+2}{3}]$$

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

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

$$\leq 2\mu^2 \left( \frac{1}{1+\epsilon} \right)^\ell \leq \frac{1}{m^2}$$

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

\[
\Pr[\text{unsuccessful} \mid \text{no cycle}]
\leq \Pr[\exists \text{ active path-structure of size at least } \frac{2\text{maxsteps}+2}{3}]
\leq \Pr[\exists \text{ active path-structure of size at least } \ell + 1]
\leq \Pr[\exists \text{ active path-structure of size exactly } \ell + 1]
\leq 2\mu^2 \left(\frac{1}{1+\epsilon}\right)^\ell \leq \frac{1}{m^2}
\]

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

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

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

and

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

Observe that

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

So far we estimated

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

and

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

Observe that

\[ \text{Pr[successful]} = \text{Pr[no cycle]} - \text{Pr[unsuccessful | no cycle]} \geq c \cdot \text{Pr[no cycle]} \]
Cuckoo Hashing

So far we estimated

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

and

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

Observe that

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

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

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

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

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

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

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

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

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

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

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

We have

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

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

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

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

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

\[
E[\text{number of steps} \mid \text{phase successful}] \\
\leq \frac{1}{c} \sum_{t \geq 1} \Pr[\text{search at least } t \text{ steps} \mid \text{no cycle}] \\
\leq \frac{1}{c} \sum_{t \geq 1} 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{(2t-1)/3} = \frac{1}{c} \sum_{t \geq 0} 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{(2(t+1)-1)/3} = O\left( \frac{1}{c} \right).
\]
Cuckoo Hashing

Hence,

\[
E[\text{number of steps} \mid \text{phase successful}]
\leq \frac{1}{c} \sum_{t \geq 1} \Pr[\text{search at least } t \text{ steps} \mid \text{no cycle}]
\leq \frac{1}{c} \sum_{t \geq 1} 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{(2t-1)/3} = \frac{1}{c} \sum_{t \geq 0} 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{(2(t+1)-1)/3}
= \frac{2\mu^2}{c(1 + \epsilon)^{1/3}} \sum_{t \geq 0} \left( \frac{1}{(1 + \epsilon)^{2/3}} \right)^t
\]
Cuckoo Hashing

Hence,

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

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

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

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

Hence,

\[
E[\text{number of steps} \mid \text{phase successful}] \\
\leq \frac{1}{c} \sum_{t \geq 1} \Pr[\text{search at least } t \text{ steps} \mid \text{no cycle}] \\
= \frac{1}{c} \sum_{t \geq 1} 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{(2t - 1)/3} = \frac{1}{c} \sum_{t \geq 0} 2\mu^2 \left( \frac{1}{1 + \epsilon} \right)^{(2(t + 1) - 1)/3} = \frac{2\mu^2}{c(1 + \epsilon)^{1/3}} \sum_{t \geq 0} \left( \frac{1}{(1 + \epsilon)^{2/3}} \right)^t = O(1) .
\]

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 $q = \Theta(1/m^2)$ (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 \( q = \Theta(1/m^2) \) (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 $q = O(1/m^2)$ (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

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

Therefore the expected cost for re-hashes is $O(m) \cdot O(p) = O(1)$. 
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 $q = O(1/m^2)$ (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 

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

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 \( q = \mathcal{O}(1/m^2) \) (probability \( \mathcal{O}(1/m^2) \) of running into a cycle and probability \( \mathcal{O}(1/m^2) \) of reaching maxsteps without running into a cycle).

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

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

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 \( q = \mathcal{O}(1/m^2) \)
(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).

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

The expected number of unsuccessful rehashes is

\[
\sum_{i \geq 1} p^i = \frac{1}{1-p} - 1 = \frac{p}{1-p} = \mathcal{O}(p).
\]

Therefore the expected cost for re-hashes is

\( \mathcal{O}(m) \cdot \mathcal{O}(p) = \mathcal{O}(1) \).
Formal Proof

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

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

$$\Pr[Y_i] \leq (m + 1) \cdot \Theta(1/m^2) \leq \Theta(1/m) =: p.$$
Formal Proof

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

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

Let $Z_i$ denote the event that the $i$-th rehash occurs:
Formal Proof

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

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

Let $Z_i$ denote the event that the $i$-th rehash occurs:

$$\Pr[Z_i] \leq \Pr[\wedge_{j=0}^{i-1} Y_j] \leq p^i$$
Formal Proof

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

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

Let $Z_i$ denote the event that the $i$-th rehash occurs:

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

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):

$$\mathbb{E}[X_i^s]$$
**Formal Proof**

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

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

Let $Z_i$ denote the event that the $i$-th rehash occurs:

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

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

$$\mathbb{E}[X_i^s] = \mathbb{E}[\text{steps} | \text{phase successful}] \cdot \Pr[\text{phase successful}] + \text{maxsteps} \cdot \Pr[\text{not successful}]$$
Formal Proof

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

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

Let $Z_i$ denote the event that the $i$-th rehash occurs:

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

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

$$E[X_i^s] = E[\text{steps} \mid \text{phase successful}] \cdot \Pr[\text{phase successful}] + \maxsteps \cdot \Pr[\text{not successful}] = O(1) .$$
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 \( X_j^s, j \geq i \) (however, it is not independent of \( X_j^s, j < i \)). Hence,

\[ E \left[ \sum_i \sum_s Z_i X_i^s \right] = \sum_i \sum_s E[Z_i] \cdot E[X_i^s] \leq O(m) \cdot \sum_i p_i \leq O(m) \cdot p_1 - p_2 = O(1) \]
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 $X_j^s$, $j \geq i$ (however, it is not independent of $X_j^s$, $j < i$). Hence,

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

$$\leq O(m) \cdot \sum_i p^i$$

$$\leq O(m) \cdot \frac{p}{1 - p}$$

$$= O(1) .$$
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 \( X_j^s, j \geq i \) (however, it is not independent of \( X_j^s, j < i \)). Hence,

\[ E\left[ \sum_i \sum_s Z_i X_i^s \right] = \sum_i \sum_s E[Z_i] \cdot E[X_i^s] \]
\[ \leq O(m) \cdot \sum_i p^i \]
\[ \leq O(m) \cdot \frac{p}{1 - p} \]
\[ = O(1) \].
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 \( X^s_j, j \geq i \) (however, it is not independent of \( X^s_j, j < i \)). Hence,

\[
E \left[ \sum_i \sum_s Z_i X^i_s \right] = \sum_i \sum_s E[Z_i] \cdot E[X^i_s] \\
\leq O(m) \cdot \sum_i p^i \\
\leq O(m) \cdot \frac{p}{1 - p} \\
= O(1) .
\]
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 \( X_j^s, j \geq i \) (however, it is not independent of \( X_j^s, j < i \)). Hence,

\[
E \left[ \sum_i \sum_s Z_i X_i^s \right] = \sum_i \sum_s E[Z_i] \cdot E[X_i^s] \\
\leq \Theta(m) \cdot \sum_i p^i \\
\leq \Theta(m) \cdot \frac{p}{1 - p} \\
= \Theta(1) .
\]
Cuckoo Hashing

**What kind of hash-functions do we need?**

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

Since maxsteps is $\Theta(\log m)$ the largest size of a path-structure or cycle-structure contains just $\Theta(\log m)$ different keys. Therefore, it is sufficient to have $(\mu, \Theta(\log m))$-independent hash-functions.
Cuckoo Hashing

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

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

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

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

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

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

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

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

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.
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 \( \frac{1}{2(1+\epsilon)} \).
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 $\frac{1}{2(1+\epsilon)}$. 