

10 van Emde Boas Trees

Dynamic Set Data Structure S :

- ▶ $S.insert(x)$
- ▶ $S.delete(x)$
- ▶ $S.search(x)$
- ▶ $S.min()$
- ▶ $S.max()$
- ▶ $S.succ(x)$
- ▶ $S.pred(x)$

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For this chapter we ignore the problem of storing satellite data:

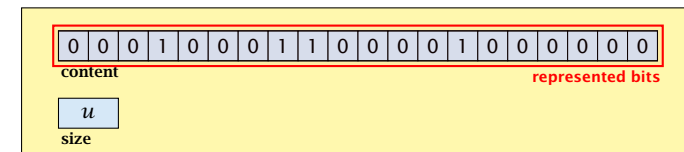
- ▶ $S.insert(x)$: Inserts x into S .
- ▶ $S.delete(x)$: Deletes x from S . Usually assumes that $x \in S$.
- ▶ $S.member(x)$: Returns 1 if $x \in S$ and 0 otherwise.
- ▶ $S.min()$: Returns the value of the minimum element in S .
- ▶ $S.max()$: Returns the value of the maximum element in S .
- ▶ $S.succ(x)$: Returns successor of x in S . Returns **null** if x is maximum or larger than any element in S . Note that x needs not to be in S .
- ▶ $S.pred(x)$: Returns the predecessor of x in S . Returns **null** if x is minimum or smaller than any element in S . Note that x needs not to be in S .

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Can we improve the existing algorithms when the keys are from a restricted set?

In the following we assume that the keys are from $\{0, 1, \dots, u-1\}$, where u denotes the size of the universe.

Implementation 1: Array



one array of u bits

Use an array that encodes the indicator function of the dynamic set.

Implementation 1: Array

Algorithm 1 array.insert(x)

```
1: content[ $x$ ]  $\leftarrow$  1;
```

Algorithm 2 array.delete(x)

```
1: content[ $x$ ]  $\leftarrow$  0;
```

Algorithm 3 array.member(x)

```
1: return content[ $x$ ];
```

- ▶ Note that we assume that x is valid, i.e., it falls within the array boundaries.
- ▶ Obviously(?) the running time is constant.

Implementation 1: Array

Algorithm 4 array.max()

```
1: for ( $i = \text{size} - 1; i \geq 0; i--$ ) do  
2:   if content[ $i$ ] = 1 then return  $i$ ;  
3: return null;
```

Algorithm 5 array.min()

```
1: for ( $i = 0; i < \text{size}; i++$ ) do  
2:   if content[ $i$ ] = 1 then return  $i$ ;  
3: return null;
```

- ▶ Running time is $\mathcal{O}(u)$ in the worst case.

Implementation 1: Array

Algorithm 6 array.succ(x)

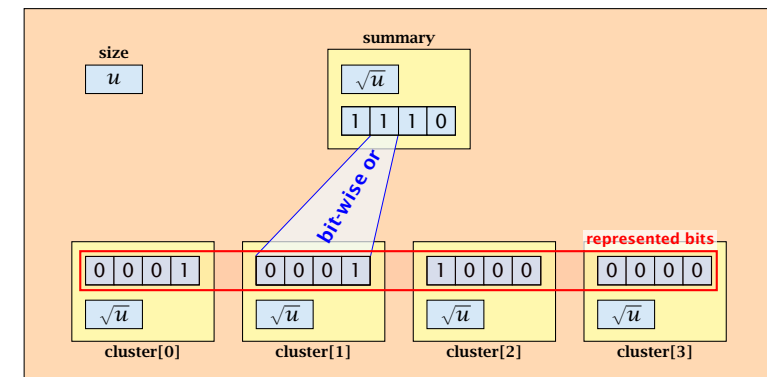
```
1: for ( $i = x + 1; i < \text{size}; i++$ ) do  
2:   if content[ $i$ ] = 1 then return  $i$ ;  
3: return null;
```

Algorithm 7 array.pred(x)

```
1: for ( $i = x - 1; i \geq 0; i--$ ) do  
2:   if content[ $i$ ] = 1 then return  $i$ ;  
3: return null;
```

- ▶ Running time is $\mathcal{O}(u)$ in the worst case.

Implementation 2: Summary Array



- ▶ \sqrt{u} cluster-arrays of \sqrt{u} bits.
- ▶ One summary-array of \sqrt{u} bits. The i -th bit in the summary array stores the bit-wise or of the bits in the i -th cluster.

Implementation 2: Summary Array

The bit for a key x is contained in cluster number $\lfloor \frac{x}{\sqrt{u}} \rfloor$.

Within the cluster-array the bit is at position $x \bmod \sqrt{u}$.

For simplicity we assume that $u = 2^{2k}$ for some $k \geq 1$. Then we can compute the cluster-number for an entry x as $\text{high}(x)$ (the upper half of the dual representation of x) and the position of x within its cluster as $\text{low}(x)$ (the lower half of the dual representation).

Implementation 2: Summary Array

Algorithm 8 member(x)

```
1: return cluster[high( $x$ )].member(low( $x$ ));
```

Algorithm 9 insert(x)

```
1: cluster[high( $x$ )].insert(low( $x$ ));  
2: summary.insert(high( $x$ ));
```

- ▶ The running times are constant, because the corresponding array-functions have constant running times.

Implementation 2: Summary Array

Algorithm 10 delete(x)

```
1: cluster[high( $x$ )].delete(low( $x$ ));  
2: if cluster[high( $x$ )].min() = null then  
3:   summary.delete(high( $x$ ));
```

- ▶ The running time is dominated by the cost of a minimum computation on an array of size \sqrt{u} . Hence, $\mathcal{O}(\sqrt{u})$.

Implementation 2: Summary Array

Algorithm 11 max()

```
1: maxcluster ← summary.max();  
2: if maxcluster = null return null;  
3: offs ← cluster[maxcluster].max();  
4: return maxcluster ◦ offs;
```

Algorithm 12 min()

```
1: mincluster ← summary.min();  
2: if mincluster = null return null;  
3: offs ← cluster[mincluster].min();  
4: return mincluster ◦ offs;
```

The operator \circ stands for the concatenation of two bitstrings.

This means if $x = 0111_2$ and $y = 0001_2$ then $x \circ y = 01110001_2$.

- ▶ Running time is roughly $2\sqrt{u} = \mathcal{O}(\sqrt{u})$ in the worst case.

Implementation 2: Summary Array

Algorithm 13 succ(x)

```

1:  $m \leftarrow \text{cluster}[\text{high}(x)]. \text{succ}(\text{low}(x))$ 
2: if  $m \neq \text{null}$  then return  $\text{high}(x) \circ m$ ;
3:  $\text{succcluster} \leftarrow \text{summary}. \text{succ}(\text{high}(x))$ ;
4: if  $\text{succcluster} \neq \text{null}$  then
5:    $\text{offs} \leftarrow \text{cluster}[\text{succcluster}]. \text{min}()$ ;
6:   return  $\text{succcluster} \circ \text{offs}$ ;
7: return null;
    
```

► Running time is roughly $3\sqrt{u} = \mathcal{O}(\sqrt{u})$ in the worst case.

Implementation 2: Summary Array

Algorithm 14 pred(x)

```

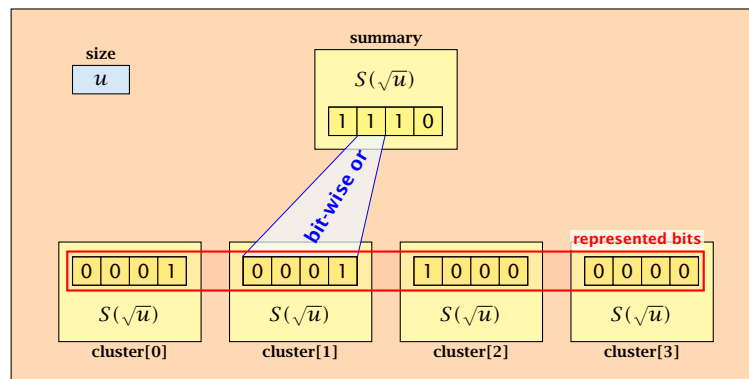
1:  $m \leftarrow \text{cluster}[\text{high}(x)]. \text{pred}(\text{low}(x))$ 
2: if  $m \neq \text{null}$  then return  $\text{high}(x) \circ m$ ;
3:  $\text{predcluster} \leftarrow \text{summary}. \text{pred}(\text{high}(x))$ ;
4: if  $\text{predcluster} \neq \text{null}$  then
5:    $\text{offs} \leftarrow \text{cluster}[\text{predcluster}]. \text{max}()$ ;
6:   return  $\text{predcluster} \circ \text{offs}$ ;
7: return null;
    
```

► Running time is roughly $3\sqrt{u} = \mathcal{O}(\sqrt{u})$ in the worst case.

Implementation 3: Recursion

Instead of using sub-arrays, we build a recursive data-structure.

$S(u)$ is a dynamic set data-structure representing u bits:



Implementation 3: Recursion

We assume that $u = 2^{2^k}$ for some k .

The data-structure $S(2)$ is defined as an array of 2-bits (end of the recursion).

Implementation 3: Recursion

The code from Implementation 2 can be used **unchanged**. We only need to redo the analysis of the running time.

Note that in the code we do not need to specifically address the non-recursive case. This is achieved by the fact that an $S(4)$ will contain $S(2)$'s as sub-datastructures, which are **arrays**. Hence, a call like `cluster[1].min()` from within the data-structure $S(4)$ is **not** a recursive call as it will call the function `array.min()`.

This means that the non-recursive case is been dealt with while initializing the data-structure.

Implementation 3: Recursion

Algorithm 15 `member(x)`

```
1: return cluster[high(x)].member(low(x));
```

► $T_{\text{mem}}(u) = T_{\text{mem}}(\sqrt{u}) + 1.$

Implementation 3: Recursion

Algorithm 16 `insert(x)`

```
1: cluster[high(x)].insert(low(x));  
2: summary.insert(high(x));
```

► $T_{\text{ins}}(u) = 2T_{\text{ins}}(\sqrt{u}) + 1.$

Implementation 3: Recursion

Algorithm 17 `delete(x)`

```
1: cluster[high(x)].delete(low(x));  
2: if cluster[high(x)].min() = null then  
3:   summary.delete(high(x));
```

► $T_{\text{del}}(u) = 2T_{\text{del}}(\sqrt{u}) + T_{\text{min}}(\sqrt{u}) + 1.$

Implementation 3: Recursion

Algorithm 18 min()

```
1: mincluster ← summary.min();
2: if mincluster = null return null;
3: offs ← cluster[mincluster].min();
4: return mincluster ◦ offs;
```

► $T_{\min}(u) = 2T_{\min}(\sqrt{u}) + 1.$

Implementation 3: Recursion

Algorithm 19 succ(x)

```
1: m ← cluster[high(x)].succ(low(x))
2: if m ≠ null then return high(x) ◦ m;
3: succcluster ← summary.succ(high(x));
4: if succcluster ≠ null then
5:   offs ← cluster[succcluster].min();
6:   return succcluster ◦ offs;
7: return null;
```

► $T_{\text{succ}}(u) = 2T_{\text{succ}}(\sqrt{u}) + T_{\min}(\sqrt{u}) + 1.$

Implementation 3: Recursion

$$T_{\text{mem}}(u) = T_{\text{mem}}(\sqrt{u}) + 1:$$

Set $\ell := \log u$ and $X(\ell) := T_{\text{mem}}(2^\ell)$. Then

$$\begin{aligned} X(\ell) &= T_{\text{mem}}(2^\ell) = T_{\text{mem}}(u) = T_{\text{mem}}(\sqrt{u}) + 1 \\ &= T_{\text{mem}}(2^{\frac{\ell}{2}}) + 1 = X\left(\frac{\ell}{2}\right) + 1. \end{aligned}$$

Using Master theorem gives $X(\ell) = \mathcal{O}(\log \ell)$, and hence $T_{\text{mem}}(u) = \mathcal{O}(\log \log u)$.

Implementation 3: Recursion

$$T_{\text{ins}}(u) = 2T_{\text{ins}}(\sqrt{u}) + 1.$$

Set $\ell := \log u$ and $X(\ell) := T_{\text{ins}}(2^\ell)$. Then

$$\begin{aligned} X(\ell) &= T_{\text{ins}}(2^\ell) = T_{\text{ins}}(u) = 2T_{\text{ins}}(\sqrt{u}) + 1 \\ &= 2T_{\text{ins}}(2^{\frac{\ell}{2}}) + 1 = 2X\left(\frac{\ell}{2}\right) + 1. \end{aligned}$$

Using Master theorem gives $X(\ell) = \mathcal{O}(\ell)$, and hence $T_{\text{ins}}(u) = \mathcal{O}(\log u)$.

The same holds for $T_{\text{max}}(u)$ and $T_{\text{min}}(u)$.

Implementation 3: Recursion

$$T_{\text{del}}(u) = 2T_{\text{del}}(\sqrt{u}) + T_{\text{min}}(\sqrt{u}) + 1 \leq 2T_{\text{del}}(\sqrt{u}) + c \log(u).$$

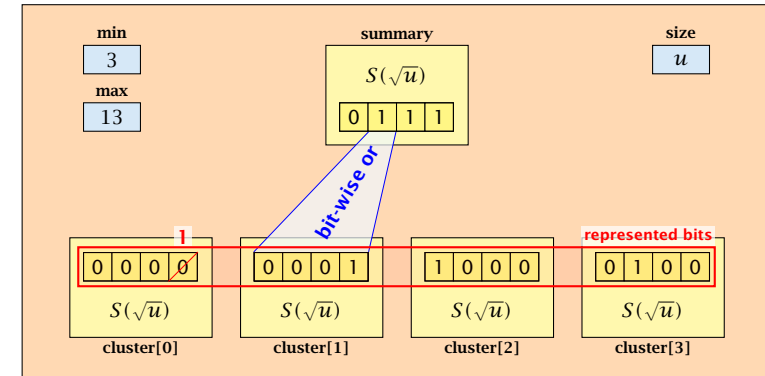
Set $\ell := \log u$ and $X(\ell) := T_{\text{del}}(2^\ell)$. Then

$$\begin{aligned} X(\ell) &= T_{\text{del}}(2^\ell) = T_{\text{del}}(u) = 2T_{\text{del}}(\sqrt{u}) + c \log u \\ &= 2T_{\text{del}}(2^{\frac{\ell}{2}}) + c\ell = 2X(\frac{\ell}{2}) + c\ell. \end{aligned}$$

Using Master theorem gives $X(\ell) = \Theta(\ell \log \ell)$, and hence $T_{\text{del}}(u) = \mathcal{O}(\log u \log \log u)$.

The same holds for $T_{\text{pred}}(u)$ and $T_{\text{succ}}(u)$.

Implementation 4: van Emde Boas Trees



- ▶ The bit referenced by **min** is **not** set within sub-datastructures.
- ▶ The bit referenced by **max** is set within sub-datastructures (if **max** \neq **min**).

Implementation 4: van Emde Boas Trees

Advantages of having max/min pointers:

- ▶ Recursive calls for **min** and **max** are constant time.
- ▶ **min = null** means that the data-structure is empty.
- ▶ **min = max \neq null** means that the data-structure contains exactly one element.
- ▶ We can insert into an empty datastructure in constant time by only setting **min = max = x**.
- ▶ We can delete from a data-structure that just contains one element in constant time by setting **min = max = null**.

Implementation 4: van Emde Boas Trees

Algorithm 20 max()

```
1: return max;
```

Algorithm 21 min()

```
1: return min;
```

- ▶ Constant time.

Implementation 4: van Emde Boas Trees

Algorithm 22 member(x)

```
1: if  $x = \text{min}$  then return 1; // TRUE
2: return cluster[high( $x$ )].member(low( $x$ ));
```

► $T_{\text{mem}}(u) = T_{\text{mem}}(\sqrt{u}) + 1 \Rightarrow T(u) = \mathcal{O}(\log \log u)$.

Implementation 4: van Emde Boas Trees

Algorithm 23 succ(x)

```
1: if  $\text{min} \neq \text{null} \wedge x < \text{min}$  then return min;
2:  $\text{maxincluster} \leftarrow \text{cluster}[\text{high}(x)].\text{max}()$ ;
3: if  $\text{maxincluster} \neq \text{null} \wedge \text{low}(x) < \text{maxincluster}$  then
4:    $\text{offs} \leftarrow \text{cluster}[\text{high}(x)].\text{succ}(\text{low}(x))$ ;
5:   return  $\text{high}(x) \circ \text{offs}$ ;
6: else
7:    $\text{succcluster} \leftarrow \text{summary}.\text{succ}(\text{high}(x))$ ;
8:   if  $\text{succcluster} = \text{null}$  then return null;
9:    $\text{offs} \leftarrow \text{cluster}[\text{succcluster}].\text{min}()$ ;
10:  return  $\text{succcluster} \circ \text{offs}$ ;
```

► $T_{\text{succ}}(u) = T_{\text{succ}}(\sqrt{u}) + 1 \Rightarrow T_{\text{succ}}(u) = \mathcal{O}(\log \log u)$.

Implementation 4: van Emde Boas Trees

Algorithm 65 insert(x)

```
1: if  $\text{min} = \text{null}$  then
2:    $\text{min} = x$ ;  $\text{max} = x$ ;
3: else
4:   if  $x < \text{min}$  then exchange  $x$  and min;
5:   if  $\text{cluster}[\text{high}(x)].\text{min} = \text{null}$ ; then
6:      $\text{summary}.\text{insert}(\text{high}(x))$ ;
7:      $\text{cluster}[\text{high}(x)].\text{insert}(\text{low}(x))$ ;
8:   else
9:      $\text{cluster}[\text{high}(x)].\text{insert}(\text{low}(x))$ ;
10:  if  $x > \text{max}$  then  $\text{max} = x$ ;
```

► $T_{\text{ins}}(u) = T_{\text{ins}}(\sqrt{u}) + 1 \Rightarrow T_{\text{ins}}(u) = \mathcal{O}(\log \log u)$.

Implementation 4: van Emde Boas Trees

Note that the recursive call in Line 7 takes constant time as the if-condition in Line 5 ensures that we are inserting in an empty sub-tree.

The only non-constant recursive calls are the call in Line 6 and in Line 9. These are mutually exclusive, i.e., only one of these calls will actually occur.

From this we get that $T_{\text{ins}}(u) = T_{\text{ins}}(\sqrt{u}) + 1$.

Implementation 4: van Emde Boas Trees

- ▶ Assumes that x is contained in the structure.

Algorithm 65 delete(x)

```
1: if min = max then
2:   min = null; max = null;
3: else
4:   if  $x = \text{min}$  then find new minimum
5:     firstcluster ← summary.min();
6:     offs ← cluster[firstcluster].min();
7:      $x \leftarrow \text{firstcluster} \circ \text{offs}$ ;
8:     min ←  $x$ ;
9:   cluster[high( $x$ )].delete(low( $x$ )); delete
10:  if cluster[high( $x$ )].min() = null then
11:    summary.delete(high( $x$ ));
continued...
```

Implementation 4: van Emde Boas Trees

Algorithm 65 delete(x)

```
...continued fix maximum
10:  if  $x = \text{max}$  then
11:    summax ← summary.max();
12:    if summax = null then max ← min;
13:    else
14:      offs ← cluster[summax].max();
15:      max ← summax ◦ offs
```

Implementation 4: van Emde Boas Trees

Note that only one of the possible recursive calls in Line 9 and Line 11 in the deletion-algorithm may take non-constant time.

To see this observe that the call in Line 11 only occurs if the cluster where x was deleted is now empty. But this means that the call in Line 9 deleted the last element in $\text{cluster}[\text{high}(x)]$. Such a call only takes constant time.

Hence, we get a recurrence of the form

$$T_{\text{del}}(u) = T_{\text{del}}(\sqrt{u}) + c .$$

This gives $T_{\text{del}}(u) = \mathcal{O}(\log \log u)$.

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Space requirements:

- ▶ The space requirement fulfills the recurrence

$$S(u) = (\sqrt{u} + 1)S(\sqrt{u}) + \mathcal{O}(\sqrt{u}) .$$

- ▶ Note that we cannot solve this recurrence by the Master theorem as the branching factor is not constant.
- ▶ One can show by induction that the space requirement is $S(u) = \mathcal{O}(u)$. Exercise.

- ▶ Let the “real” recurrence relation be

$$S(k^2) = (k + 1)S(k) + c_1 \cdot k; S(4) = c_2$$

- ▶ Replacing $S(k)$ by $R(k) := S(k)/c_2$ gives the recurrence

$$R(k^2) = (k + 1)R(k) + ck; R(4) = 1$$

where $c = c_1/c_2 < 1$.

- ▶ Now, we show $R(k) \leq k - 2$ for squares $k \geq 4$.

- ▶ Obviously, this holds for $k = 4$.
- ▶ For $k = \ell^2 > 4$ with ℓ integral we have

$$\begin{aligned} R(k) &= (1 + \ell)R(\ell) + c\ell \\ &\leq (1 + \ell)(\ell - 2) + \ell \leq k - 2 \end{aligned}$$

- ▶ This shows that $R(k)$ and, hence, $S(k)$ grows linearly.

van Emde Boas Trees

Bibliography

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

See Chapter 20 of [CLRS90].