

# B-trees

What they are

How they are implemented

## B-trees

Self-balancing **search trees**

Fast **search, insertion, deletion**

Widely used for **databases** and **file systems**

Introduced by **Bayer & McCreight** (1970)  

What does **B** stand for? **Balanced?** **Bushy?** **Boeing?**

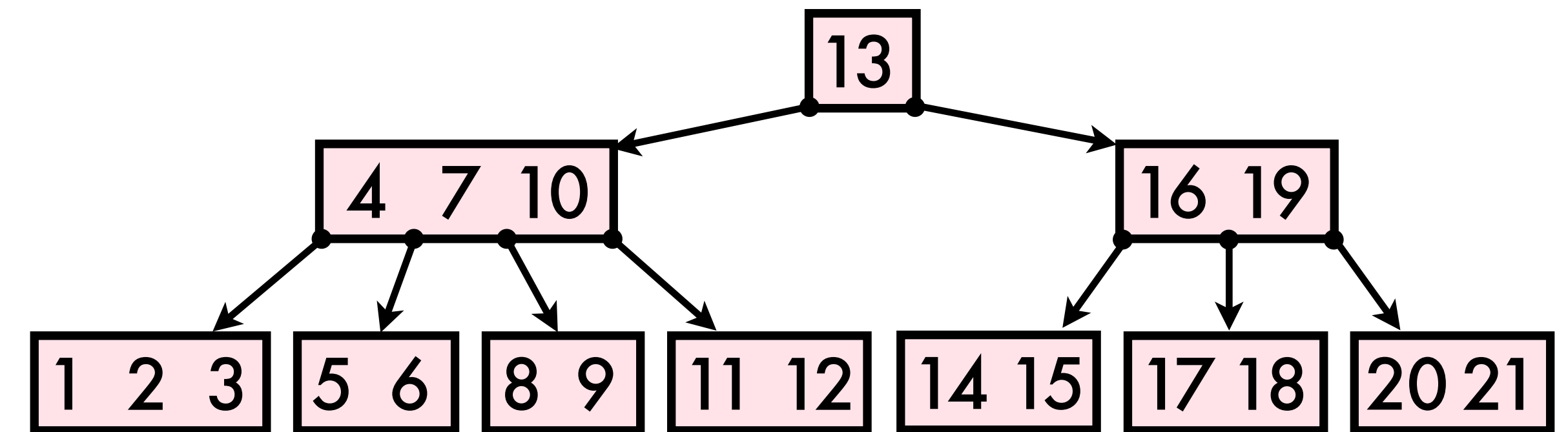
*"The more you think about what the **B** could mean, the more you learn about B-trees"* (Bayer)

B-tree complexity (for  $n$  data items)

**Worst case:** **search, insert, delete**  $\rightarrow O(\log n)$

**Storage** of B-trees:  $\Theta(n)$

**B-trees:** **Balanced search trees** where nodes can have **many children** (e.g. thousands)



**Higher branching factor**  $\Rightarrow$  **Reduced tree height**

$\Rightarrow$  **Fewer disk accesses**

Example applications: **MySQL** **ApFS** **btrfs**

References/Notes/Image credits:

R. Bayer and E. McCreight, "Organization and maintenance of large ordered indices", ACM SIGFIDET (1970)

(R. Bayer) [https://www.computerhope.com/people/rudolf\\_bayer.htm](https://www.computerhope.com/people/rudolf_bayer.htm)

(E. McCreight photo and discussion of naming) [https://www.mccreight.com/people/ed\\_mcc/index.htm](https://www.mccreight.com/people/ed_mcc/index.htm)

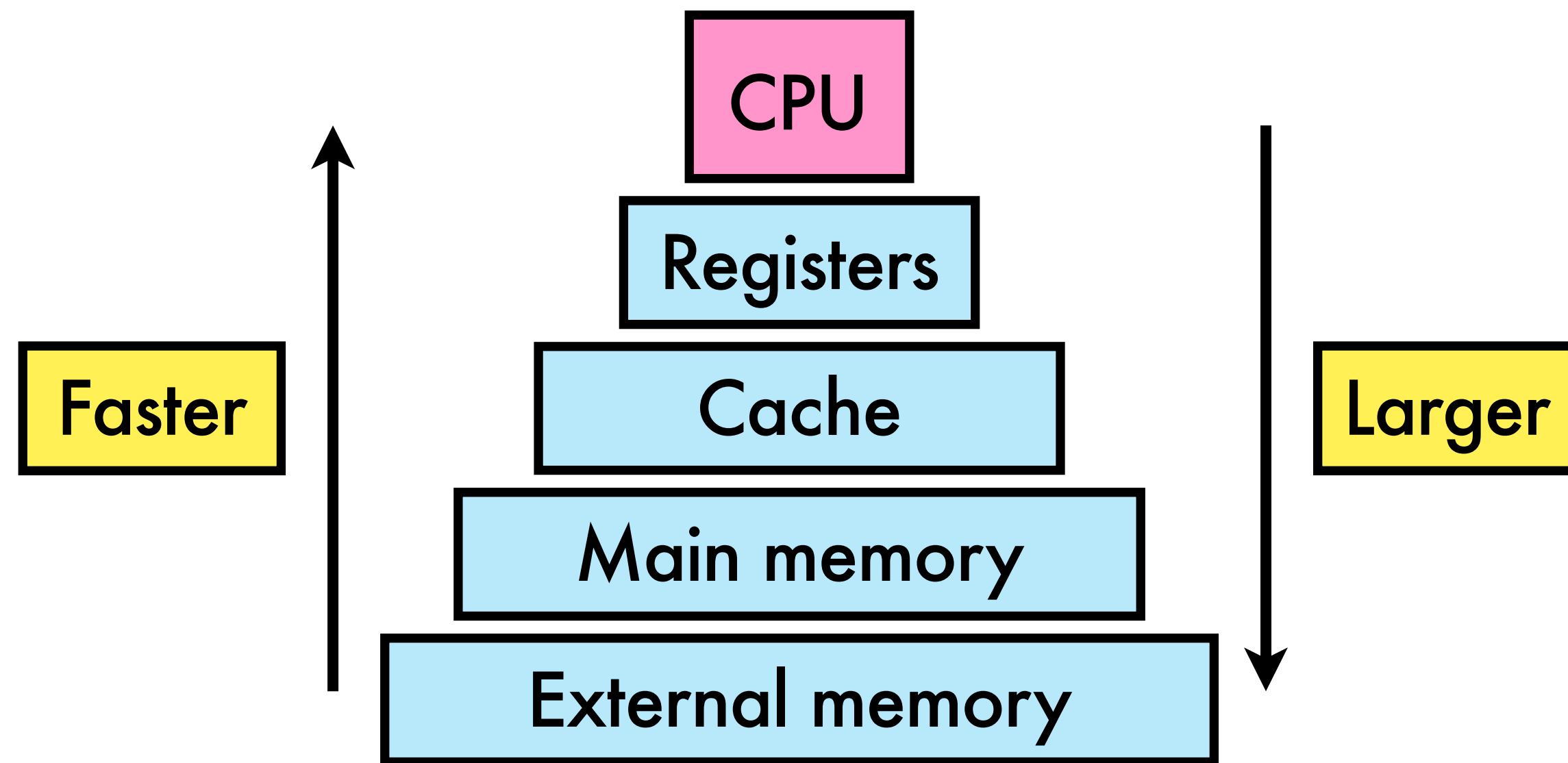
(B-tree use in MySQL) <https://www.vertabelo.com/blog/all-about-indexes-part-2-mysql-index-structure-and-performance/>

(B-tree use in ApFS) <https://www.ntfs.com/apfs-structure.htm>

(B-tree use in btrfs) <https://en.wikipedia.org/wiki/Btrfs>

# Precursor: Memory Hierarchy/External Memory

Computer memory is arranged as a hierarchy



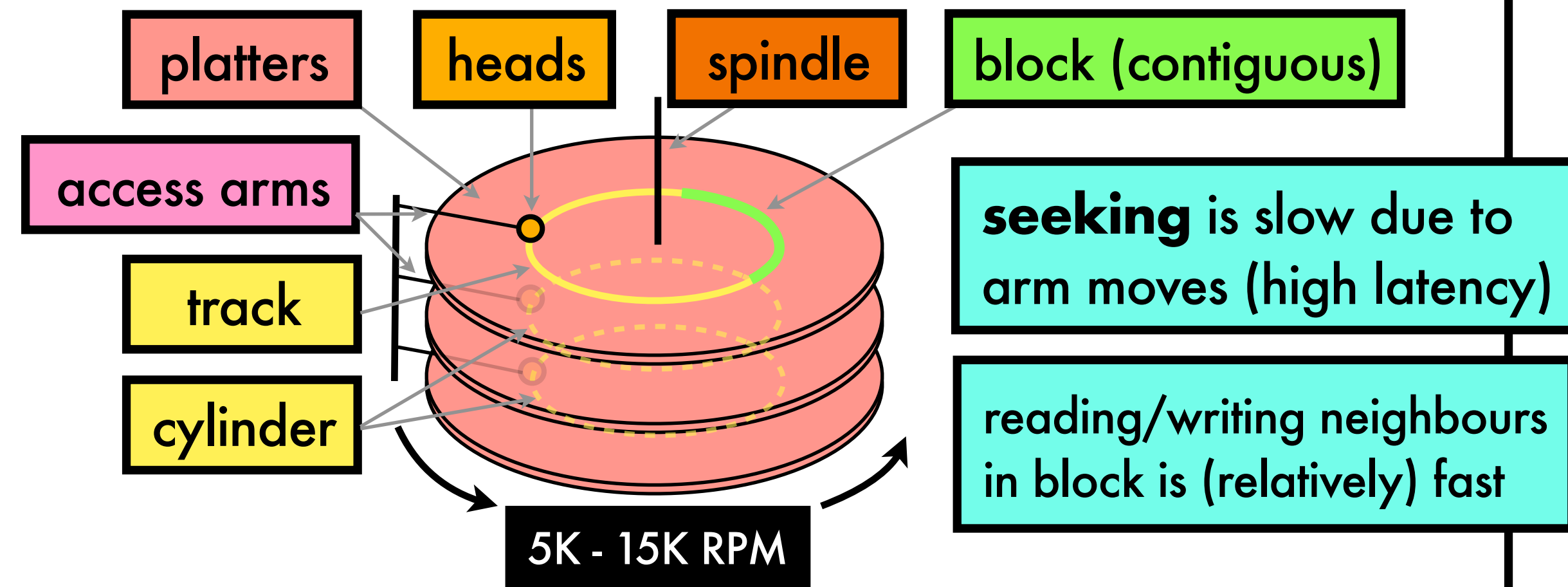
For many problems, we care about **two levels**:

- The level that can store **all items** in the problem
- The **level above this** Transfer is often the bottleneck

**B-trees** are well-suited to addressing this challenge

Focus on **External memory** ↔ **Main memory**

**Hard Disk Drive** (introduced in 1956)



**SSDs**: **lower latency** than **HDDs**, but still higher than **main memory** (both **SATA SSD** & **NVMe SSD**)  
SSDs also use **blocks** for **data access**

## References:

(Memory hierarchy) M. T. Goodrich et al., "Algorithm design and applications", Chap. 20 (2015)  
(Introduction of HDD in 1956) [https://www.ibm.com/ibm/history/exhibits/storage/storage\\_350.html](https://www.ibm.com/ibm/history/exhibits/storage/storage_350.html)

D. E. Knuth, "The art of computer programming, vol. 3: sorting and searching", Chap. 5.4.9 (1998)  
T. Cormen et al., "Introduction to algorithms", Chap. 18, MIT press (2022)

# B-trees and Counting Disk Accesses

## A key idea for B-trees:

Make **number of children** as **large as possible** while ensuring each **node** fits in a **single block**

Navigating down a **shallow-but-wide** B-tree then involves **very few disk accesses**

**Example:** Suppose we have **200 children** (**199 keys**) at each **internal node**

A (full) B-tree with **depth 3** will contain  $1 + 200 + 200^2 + 200^3 = 8040201$  nodes

If we keep the **root node** in memory, we can access  $\approx 1.6\text{B}$  keys with just **three disk accesses!**

## Counting disk accesses

**Reading/writing** blocks from **disk** is **expensive**, so we track both: **CPU time** **Disk block read/writes**

To access an object **u** that is not in memory, we must **read** the **block** that contains it **read\_block(u)**

To store changes to **u**, we need to **write** its **block** to disk **write\_block(u)**

### References:

M. T. Goodrich et al., "Algorithm design and applications", Chap. 20 (2015)

T. Cormen et al., "Introduction to algorithms", Chap. 18, MIT press (2022)

Note: A similar cost model for counting disk accesses (based on page accesses) is described in detail by R. Sedgwick et al., "Algorithms", 4th Ed. (2011)

## B-tree properties (based on CLRS)

A **B-tree** is a tree with **minimum degree,  $t$** :

- Node  **$u$**  has attributes:

**$u.keys$**  **list** (ascending order)  **$u.is\_leaf$**

- **Internal** node  **$u$**  has  **$\text{len}(keys) + 1$  children**

**$u.children$**  **list of length  $\text{len}(keys) + 1$**

- The keys of node  **$u$**  **separate** its **children's keys**

**$u.keys[i] \leq u.children[i+1].keys[j] \leq u.keys[i+1]$**   **$\forall$  valid  $j$**

**$u.children[0].keys[j] \leq u.keys[0]$**   **$u.keys[-1] \leq u.children[-1].keys[j]$**

- All leaves have the **same depth**
- All nodes (except **root**) have  **$\geq t - 1$  keys**
- All nodes have  **$\leq 2t - 1$  keys**

When  $t = 2$ , the B-tree is called a **2-4 tree** or **2-3-4 tree**

# B-tree Definition

**Warning:** there are many **different** notation/definition conventions for **B-trees**!

Bayer & McCreight

Knuth (TAOCP)

CLRS

The height of an  **$n$ -key** B-tree grows  $\Theta(\log n)$

Num. **nodes** in a max height ("**skinny**") tree

$$= \text{root} + 1 + 2 + 2t + 2t^2 + \dots = 1 + 2 \left( \frac{t^h - 1}{t - 1} \right)$$

$$\text{Num. keys } n = 1 + (t - 1) \cdot 2 \left( \frac{t^h - 1}{t - 1} \right) = 2t^h - 1$$

$$\Rightarrow h_{\max} = \left\lfloor \log_t \left( \frac{n + 1}{2} \right) \right\rfloor$$

**Floor  $\lfloor \cdot \rfloor$**  for other  $n$  values

**Note: base  $t$  in the log makes B-trees short!**

If  $t$  fixed, use  $\Theta(\log n)$  not  $\Theta(\log_t n)$  (base change is **constant factor**)

References:

R. Bayer and E. McCreight, "Organization and maintenance of large ordered indices", ACM SIGFIDET (1970)

D. E. Knuth, "The art of computer programming, vol. 3: sorting and searching", Chap. 6.2.4 (1998)

(CLRS) T. Cormen et al., "Introduction to algorithms", Chap. 18.1, MIT press (2022)

(2-3-4 trees) [https://en.wikipedia.org/wiki/2-3-4\\_tree](https://en.wikipedia.org/wiki/2-3-4_tree)

M. T. Goodrich et al., "Algorithm design and applications", Chap. 20.2 (2015)



# B-tree Search

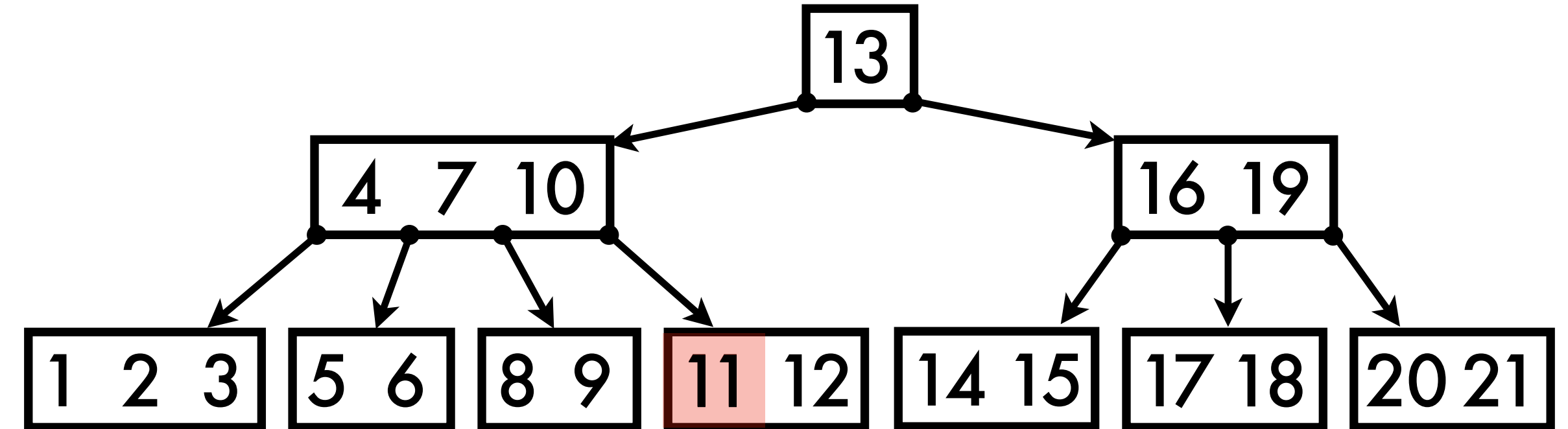
Python B-tree **search** procedure (recursive):

```
def search(self, u, key): # u is a node
    # linear scan to find index of key
    i = 0
    while i < len(u.keys) and key > u.keys[i]:
        i += 1
    if i < len(u.keys) and key == u.keys[i]:
        return (u, i)
    if u.is_leaf:
        return None
    read_block(u.children[i])
    return self.search(u.children[i], key)
```

Arguments: (root, 11)

Returns (node, 0)

Could replace **linear scan** with **binary search**  
(not always useful due to **caching effects**)



Example B-tree

## Search complexity

Consider costs with **min. degree**,  $t$  and **num. keys**,  $n$

We've seen that tree height is  $O(\log_t n)$  for  $n$  keys

**CPU** **Linear scan**  $O(t)$  per node,  $O(t \log_t n)$  total

(or with **binary search**,  $O(\log_2 t \log_t n) = O(\log_2 n)$ )

**Disk block reads**  $O(\log_t n)$

References:

(CLRS) T. Cormen et al., "Introduction to algorithms", Chap. 18.2, MIT press (2022)

(Current Linux B+-tree - uses linear scans) <https://github.com/torvalds/linux/blob/7f317d34906c1033f0752fc137dda04e43979bb8/include/linux/btree.h>

# B-tree Insertion

## Overview of strategy

Idea: **search** for leaf node and **insert key**

What if that node is **already full**?

**Split** full node into **two nodes** at **median key**:

Keys to left of **median key** go to the first

Keys to right of **median key** go to the second

Move **median key** up into **parent**

What if the **parent** is **already full**...?

**Two strategies** for **B-tree insertion**:

1. **"Insert-then-fix"** (Bayer & McCreight)

Insert at leaf, then **reverse up tree** and **fix**

2. **"Fix-then-insert"** (CLRS) **Split full nodes** on

the **way down**, then insert at leaf **Benefit: "1 pass"**

Insert complexity **CPU**  $O(t \log_t n)$  **Disk**  $O(\log_t n)$

### References:

R. Bayer and E. McCreight, "Organization and maintenance of large ordered indices", ACM SIGFIDET (1970)

(CLRS) T. Cormen et al., "Introduction to algorithms", Chap. 18.2, MIT press (2022)

L. Xinyu, "Elementary Algorithms", Chap. 7 (2022)

# B-tree Deletion

## Overview of strategy

Idea: **search** for node and **delete** key

What if that node **becomes too small**?

"**Fix-then-delete**" - only (recursively) call delete

on nodes with  $\geq t$  keys (safe to delete 1) **1 pass**

This means we may need to **transfer a key down** into a child **before calling delete**

OK since we ensure current node has  $t$  keys!

There are **3 cases** to handle - when **search**:

1. Reaches **leaf node**
2. Reaches **internal node** containing target key
3. Reaches **internal node** without target key

References:

(CLRS) T. Cormen et al., "Introduction to algorithms", Chap. 18.3, MIT press (2022)

SA Implement B-tree deletion in Python

< 2 / 2 > Here's an implementation of B-tree deletion in Python: 

```
python
Copy code

class BTreeNode:
    def __init__(self, keys=[], children=[], is_leaf=True, max_num_keys=5):
        self.keys = keys
        self.children = children
        self.is_leaf = is_leaf
        if max_num_keys < 3: # max_num_keys must be odd and greater or equal to 3
            max_num_keys = 3
        if max_num_keys % 2 == 0: # max_num_keys must be odd
            max_num_keys += 1
        self.max_num_keys = max_num_keys

    def is_full(self):
        return len(self.keys) >= self.max_num_keys

class BTree:
    def __init__(self, max_num_keys=5):
        self.max_num_keys = max_num_keys
        self.root = BTreeNode(max_num_keys=max_num_keys)

    def find_leaf(self, key, node=None):
        if node is None:
            node = self.root
        if node.is_leaf:
            return node
        for i in range(len(node.keys)):
            if key < node.keys[i]:
                return self.find_leaf(key, node.children[i])
        return self.find_leaf(key, node.children[len(node.keys)])

    def remove(self, key):
        leaf = self.find_leaf(key)
        if key in leaf.keys:
            self.remove_from_leaf(leaf, key)

    def remove_from_leaf(self, leaf, key):
        index = leaf.keys.index(key)
        del leaf.keys[index]
        if len(leaf.keys) < self.max_num_keys // 2:
            self.repair_leaf(leaf)

    def repair_leaf(self, leaf):
        if self.root == leaf:
            if not leaf.keys:
                self.root = None
            return
        parent = self.find_parent(leaf)
        index = parent.children.index(leaf)
        if index > 0 and len(parent.children[index - 1].keys) > self.max_num_keys // 2:
            self.borrow_from_prev_leaf(leaf, parent, index)
        elif index < len(parent.keys) and len(parent.children[index + 1].keys) > self.max_num_keys // 2:
            self.borrow_from_next_leaf(leaf, parent, index)
        else:
            if index > 0:
                self.merge_with_prev_leaf(leaf, parent, index)
            else:
                self.merge_with_next_leaf(leaf, parent, index)

    def borrow_from_prev_leaf(self, leaf, parent, index):
        prev_leaf = parent.children[index - 1]
        key = prev_leaf.keys[-1]
        prev_leaf.keys = prev_leaf.keys[:-1]
        leaf.keys = [key] + leaf.keys

    def borrow_from_next_leaf(
```

L. Xinyu, "Elementary Algorithms", Chap. 7 (2022)

# B-tree Deletion - Complexity

## Deletion complexity (one pass)

Successor/predecessor calls followed by function termination (still "one pass")

Tree height is  $O(\log_t n)$  for  $n$  keys:

**CPU** Linear scan  $O(t)$  per node,  $O(t \log_t n)$  total

**Disk block reads/writes**  $O(\log_t n)$

Note: in practice, most deleted keys are in the leaves (for large values of  $t$ )

Other B-tree variants we did not discuss:

**B+-tree** - all values stored in leaves (not internal nodes) which are linked

**B\*-tree** - aims to keep non-root nodes "more full" (at least 2/3)

### References:

(CLRS) T. Cormen et al., "Introduction to algorithms", Chap. 18.3, MIT press (2022)

L. Xinyu, "Elementary Algorithms", Chap. 7 (2022)

D. Comer, "The Ubiquitous B-tree", ACM Computing Surveys (1979)

D. E. Knuth, "The art of computer programming, vol. 3: sorting and searching", Chap. 6.2.4 (1998)



# Hash tables

What they are

How they are implemented

## Hash tables

Data structures for fast **search**, **insertion** & **deletion**

Introduced by **H. P. Luhn** at IBM (1953) 

### Complexity (for $n$ data items)

In typical conditions, hash tables **ops** are **fast**:

**Avg. case**: **search**, **insert**, **delete**  $\rightarrow O(1)$

key  
benefit

**Worst case**: **search**, **insert**, **delete**  $\rightarrow \Theta(n)$

**Storage complexity** of hash tables:  $\Theta(n)$

Suited for **Abstract Data Types**

**Set**

**Map**

References/Notes/Image credits:

H. Stevens, "Hans Peter Luhn and the birth of the hashing algorithm", IEEE spectrum (2018)

(Luhn photo) [https://researcher.watson.ibm.com/researcher/view\\_page.php?id=6990](https://researcher.watson.ibm.com/researcher/view_page.php?id=6990)

"Associative Array"/"Dictionary" can replace "Map" [https://en.wikipedia.org/wiki/Associative\\_array](https://en.wikipedia.org/wiki/Associative_array)

# Idea: search by index

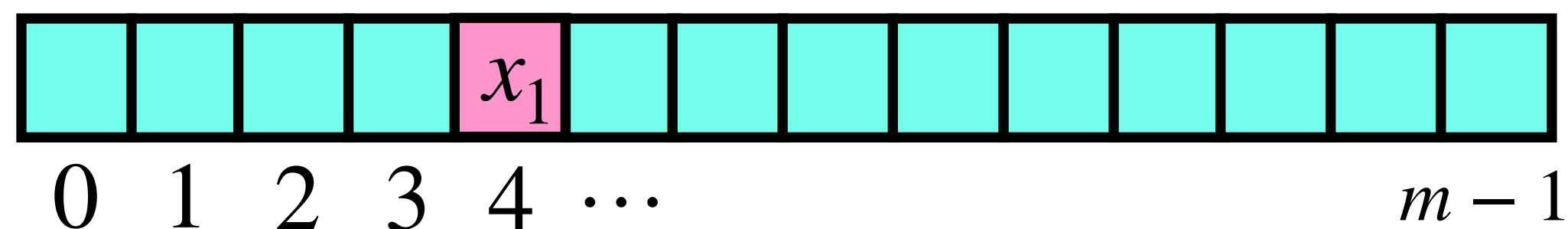
**Idea:** replace search with **array indexing**  $O(1)$

Direct-address table

Suppose the  $n$  objects  $x_0, \dots, x_{n-1}$  we'll store have **unique integer keys**  $k_0, \dots, k_{n-1}$

$k_i \in \{0, \dots, m-1\}$  Universe,  $U$ , is set of possible keys

Build a **big array** with  $m$  slots:  $U = \{0, \dots, m-1\}$



Unused slots have a value of **None**:

Example operations on  $x_0$  ( $k_0 = 2$ )  $x_1$  ( $k_1 = 4$ )

**Insert**  $x_0, x_1$

**delete**  $x_0$

**search**  $k = 4$

We **search**, **insert**, **delete** using array in  $O(1)$

What happens if  $|U| \gg n$ ? **Lots of wasted space!**

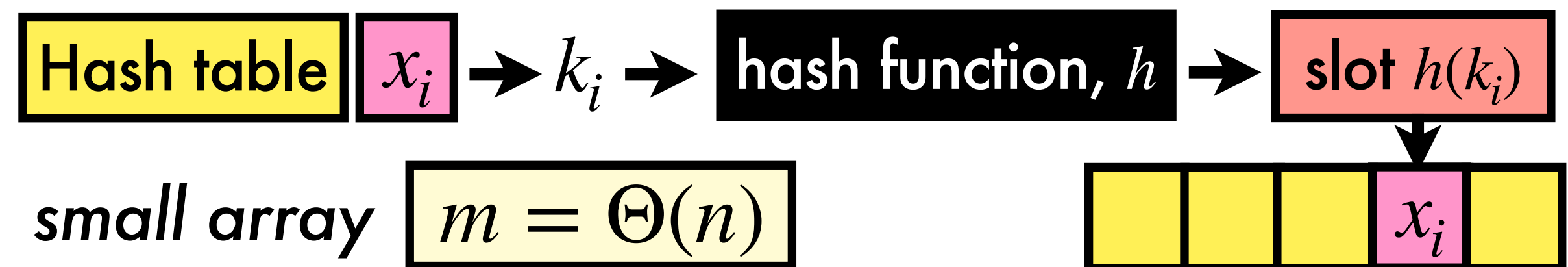
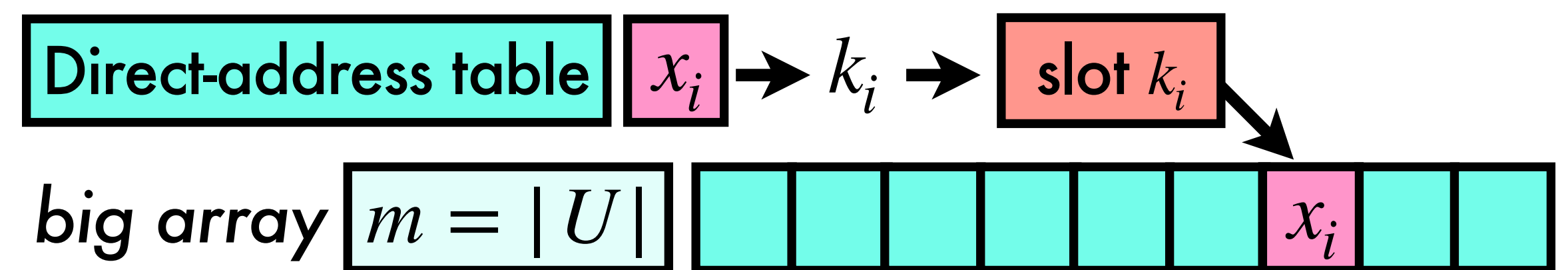
Suppose we want to store 5 **IPv6 addresses**

Our **universe size** is  $|U| = 2^{128}$

$> 1\text{K trillion trillion}$  1TB hard drives!  $> 28 \cdot 10^{27}$  GBP

A **hash table** uses a function,  $h$ , to compute slots  
 $h : U \rightarrow \{0, \dots, m-1\}$  is a **hash function**

**Goal:** design  $h$  to shrink array size ( $m = \Theta(n)$ )

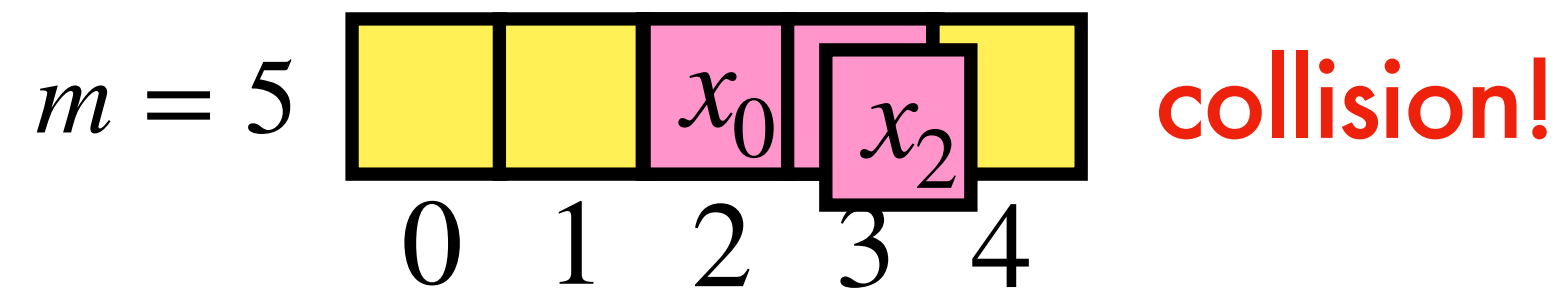


# Hash functions

"Input data is not random! So good hash functions must be random!" J. Erickson

Suppose  $U \subset \mathbb{Z}$  and our hash table has  $m$  slots

A basic **hash function**:  $h(k) = k \bmod m$



$x_0$  ( $k_0 = 2$ )     $x_1$  ( $k_1 = 8$ )     $x_2$  ( $k_2 = 23$ )

Two key **requirements** for our hash function:

1. Fast to **compute**

2. Minimise **collisions**  $h(k_i) = h(k_j)$  with  $k_i \neq k_j$

**Ideal**  $h(k)$  rolls a fair  $m$ -sided die for each  $k$ :  
an **independent uniform random hash function**

How to get **randomness** from **nonrandom data**?

## Division method

Static

$h(k) = k \bmod m$   
helps (a bit) if  $m$  is prime

## Multiplication method

Choose  $A \in (0,1)$   
 $h(k) = \lfloor m \cdot (Ak \bmod 1) \rfloor$

vulnerable to unfavourable key distributions (many collisions)

**Universal** family  $H$ :

Random

$$P_{h \in H}[h(k_i) = h(k_j)] \leq \frac{1}{m} \quad \forall i \neq j$$

## A universal family

Pick a **prime number**  $p > |U|$

$$h_{a,b}(x) \triangleq ((ax + b) \bmod p) \bmod m$$

$$H_{p,m} = \{h_{a,b} \mid a \in \mathbb{Z}_p^*, b \in \mathbb{Z}_p\}$$

( $a, b$  are "**salts**")

less vulnerable

## Cryptographic

**Pre-image** resistance

**Collision** resistance

(typically **slower**)

## Applications

Hash tables

String search

Passwords

Signatures

Digests

Proof-of-work



# Chaining

**Chaining:** a simple way to handle collisions

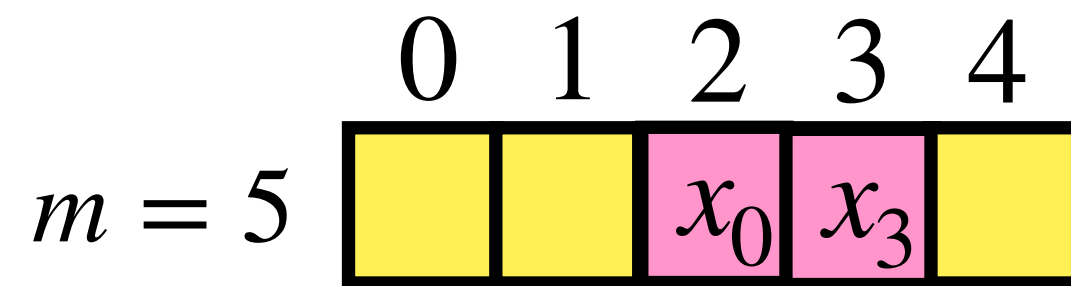
**Insert**

$x_0$  ( $k_0 = 2$ )

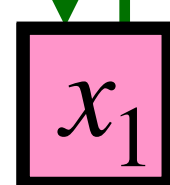
$x_1$  ( $k_1 = 8$ )

$x_2$  ( $k_2 = 23$ )

$x_3$  ( $k_3 = 98$ )



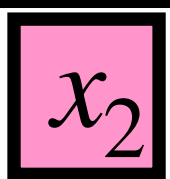
Doubly-linked list



$$h(k) = k \bmod m$$

**Search** for ( $k = 8$ )

**Delete**



Worst case scenario (for search)

All  $n$  keys **collide**  $\implies$  all objects in same slot

Search is then  $\Theta(n)$  with **linked lists**

( $\Theta(\log n)$  if lists are **ordered** for binary search)

Average scenario (cost of unsuccessful search)

Define the **load factor** of table:  $\alpha \triangleq \frac{n}{m}$  items / slots

Assume our hash function is **universal**

**Collision probability**  $\leq 1/m$

$$\mathbb{E}(\text{chain length}) = n/m = \alpha$$

**Average cost:**  $\Theta(1 + \alpha)$  (hashing + chain search)

Average cost of successful search

Similarly to **unsuccessful search**:  $\Theta(1 + \alpha)$

References/Notes:

See J. Erickson, "Algorithms" <http://algorithms.wtf/> "Lecture 5: Hash Tables" (2019) for a more detailed proof or T. Cormen et al., "Introduction to algorithms" MIT press, Chap 11.2 (2022) for an extended analysis



# Open addressing

**Open addressing:** chain-free collision handling

Coined by William W. Peterson in 1957 

The simplest variant is linear probing:

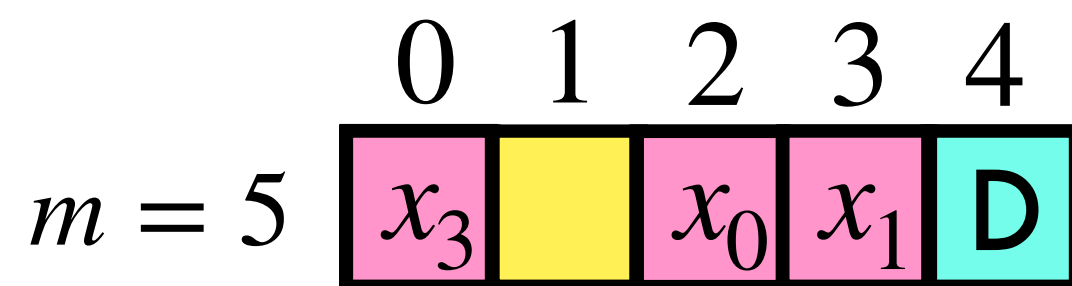
**Insert**

$x_0$  ( $k_0 = 2$ )

$x_1$  ( $k_1 = 8$ )

$x_2$  ( $k_2 = 23$ )

$x_3$  ( $k_3 = 98$ )



primary clustering

$$h(k) = k \bmod m$$

**Search for** ( $k = 98$ )

**Delete**  $x_2$

**Probe sequences**

**Open addressing schemes**

produce permutation of  $(0, 1, \dots, m - 1)$

**Double hashing:**  $h(k, i) = (h_1(k) + i h_2(k)) \bmod m$   
position in probe sequence

For a permutation,  $h_2(k)$  and  $m$  must be coprime

Analysis: number of probes in unsuccessful search ( $\alpha < 1$ )

Assume independent uniform permutation hashing

Max probes:  $\frac{1}{1 - \alpha} = 1 + \alpha + \alpha^2 + \alpha^3 + \dots$

at least one    more than 1    more than 2    more than 3

References/Notes/Image credits:

D. E. Knuth, "The art of computer programming, vol. 3: sorting and searching", Chap 6.4, (1974)

W. W. Peterson, "Addressing for random-access storage." IBM journal of Research and Development (1957)

[https://en.wikipedia.org/wiki/W.\\_Wesley\\_Peterson#/media/File:W.\\_Wesley\\_Peterson.jpg](https://en.wikipedia.org/wiki/W._Wesley_Peterson#/media/File:W._Wesley_Peterson.jpg)

(Open addressing) T. Cormen et al., "Introduction to algorithms", Chap 11.4, MIT press, (2022)