Algorithms and Data Structures (II)

Gabriel Istrate

May 20, 2020

Where are we:

Graphs: Representations and Algorithms

- Continue with Minimum Spanning Tree.
- Data Structures for external memory: B-Trees.

Minimum Spanning Tree: Algorithms

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- Kruskal's algorithm (1956)
 - based on the generic minimum-spanning-tree algorithm (last time)
 - ► incrementally builds a *forest* A

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 - incrementally builds a *forest* A
- Prim's algorithm (1957)
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 - incrementally builds a single tree A

Disjoint-Set Data Structure

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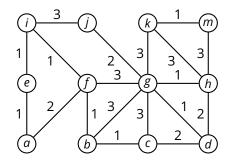
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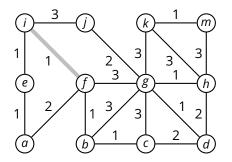
■ Union(x, y) joins the sets containing x and y

MST-KRUSKAL(G, w)

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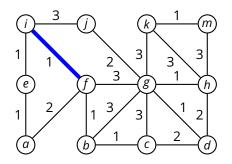
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$$A = A \cup \{(u, v)\}$$

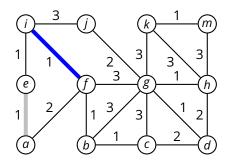


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 $A = \emptyset$ **for** each vertex $v \in V(G)$ **Make-Set**(v) *// disjoint-set* data structure 4 sort *E* in non-decreasing order by weight *w* **for** each edge $(u, v) \in E$, taken in non-decreasing order by *w* **if** FIND-SET $(u) \neq$ FIND-SET(v)

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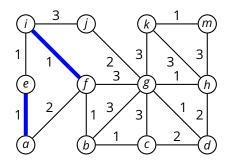


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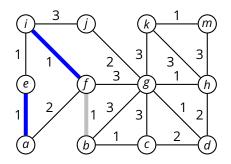
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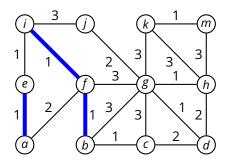


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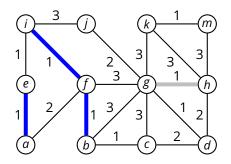
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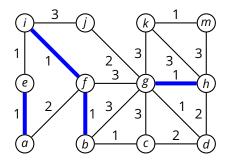


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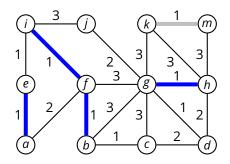


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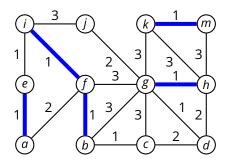


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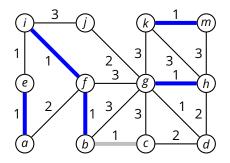


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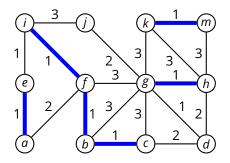


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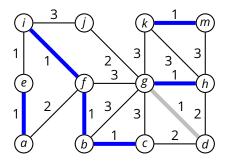
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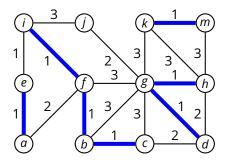
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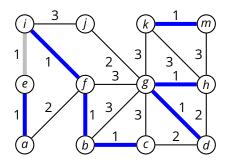
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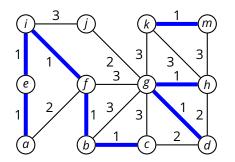
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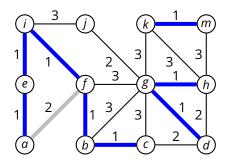
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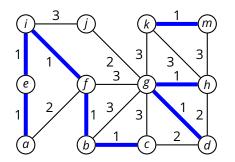
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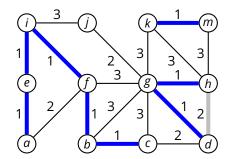
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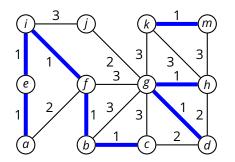
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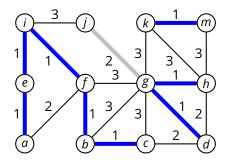
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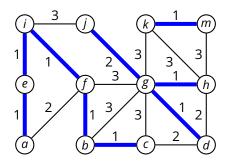


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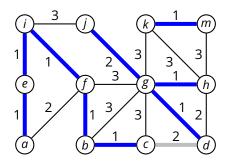
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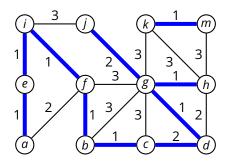


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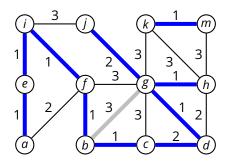
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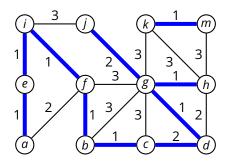


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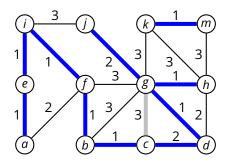


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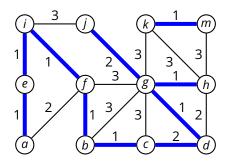


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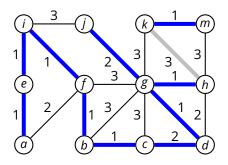
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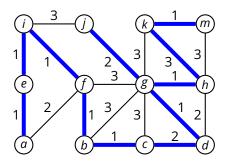
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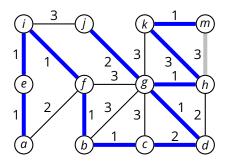
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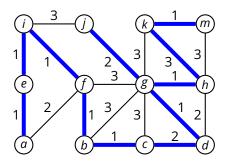
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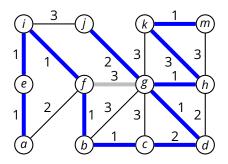
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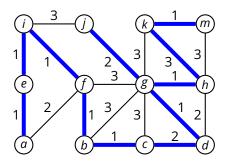
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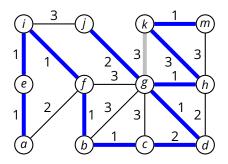
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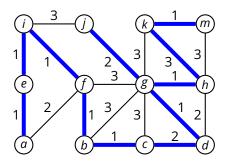
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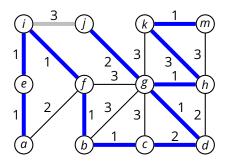
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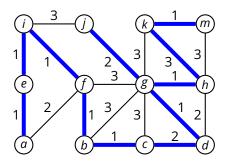
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- 2|*E*| times **FIND-SET**

MST-KRUSKAL(G, w) $A = \emptyset$ **for** each vertex $v \in V(G)$ 2 3 **MAKE-SET**(v)// disjoint-set data structure sort E in non-decreasing order by weight w 4 **for** each edge $(u, v) \in E$, taken in non-decreasing order by w 5 **if** FIND-SET $(u) \neq$ FIND-SET(v)6 7 $A = A \cup \{(u, v)\}$ UNION(u, v)8

- |*V*| times **MAKE-SET** (loop of line 2–3)
- $O(|E| \log |E|)$ for sorting *E* (line 4)
- 2|*E*| times **FIND-SET**
- O(|E|) times UNION

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- Can be done (complicated way) so that complexity of Kruskal: *O*(*Elog*(*V*)).

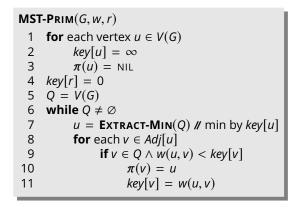
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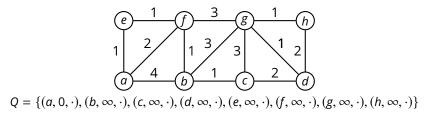
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- "Union-by-rank" and "path compression" heuristics.
- Cormen: Chapter 21.

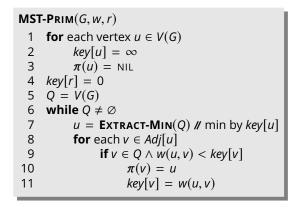
Remember

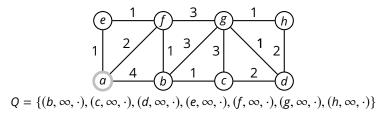
- In Kruskal's algorithm: grow a forest.
- In Prim's algorithm: grow a tree.
- Use: min-priority queue.
- Remember ? First semester. Implemented using heaps.
- Elements have "priorities". An element with high priority is served before an element with low priority.
- Operations:
- IS_EMPTY: *O*(1).
- INSERT_WITH_PRIORITY: $O(\log n)$.
- POP: $O(\log n)$.
- PEEK: *O*(1).
- (BUILD): *O*(*n*).
- ADVANCED: Can improve over the heap implementation !

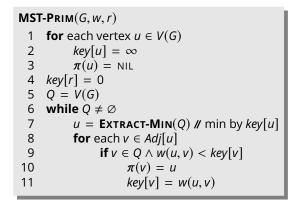
```
MST-PRIM(G, w, r)
     for each vertex u \in V(G)
  1
 2
3
          key[u] = \infty
           \pi(u) = \text{NIL}
 4
    key[r] = 0
 5 Q = V(G)
  6
    while Q \neq \emptyset
 7
           u = \text{Extract-Min}(Q) / min by key[u]
 8
9
           for each v \in Adj[u]
                if v \in Q \land w(u, v) < key[v]
10
                      \pi(v) = u
                      key[v] = w(u, v)
11
```

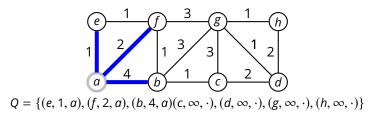


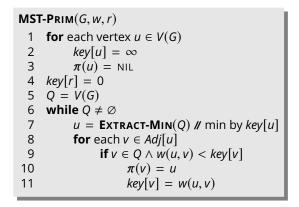


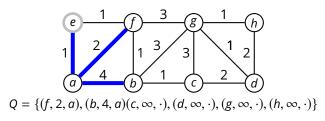


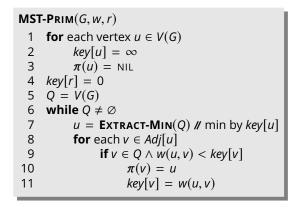


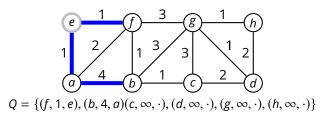


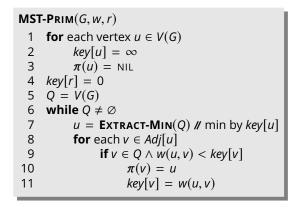


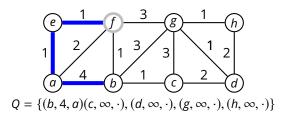


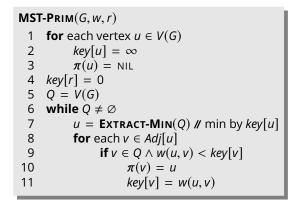


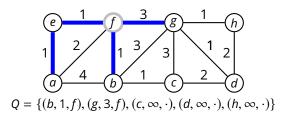


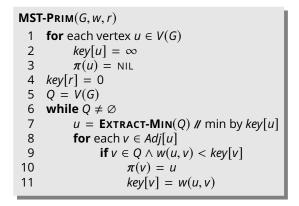


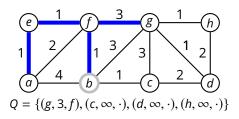


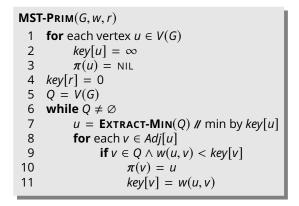


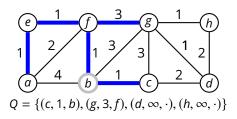


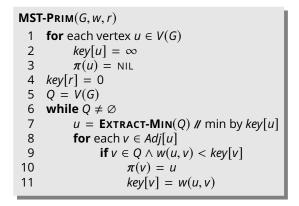


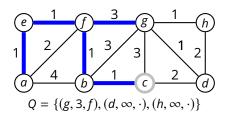


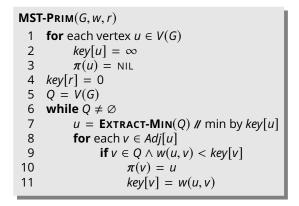


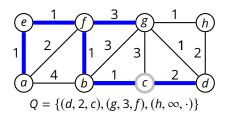


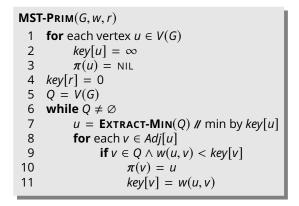


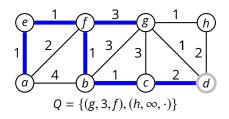


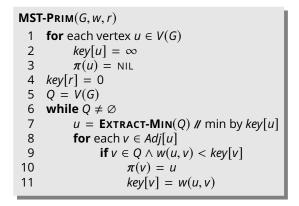


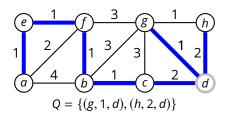


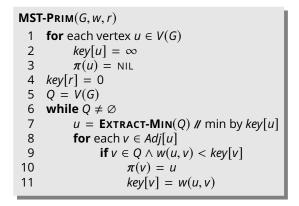


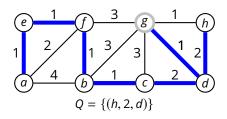


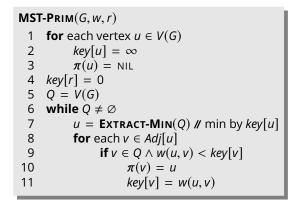


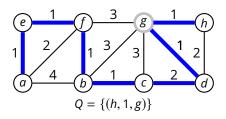


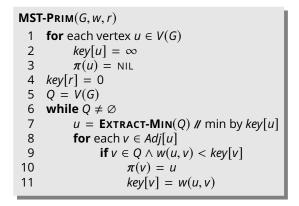


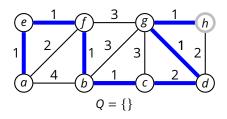


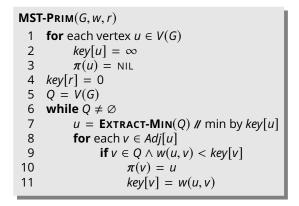


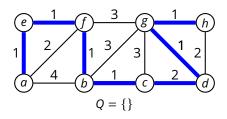












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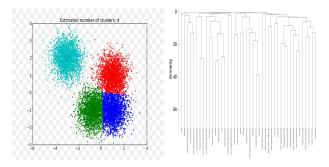
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- Cormen: Chapter 20 (Fibonacci heaps).

• One answer: neat greedy algorithms.

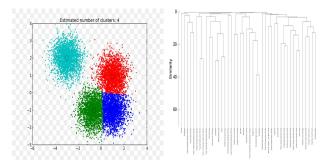
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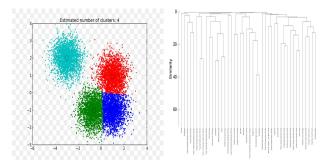
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- Where do we go from here ? Matroids. "Abstract" formalism that generalizes vector spaces and spanning trees (!). Cormen, 16.4.



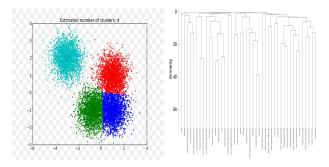
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- Why not stop when there are k clusters? (or compute MST and remove heaviest edges)?

Next: B-Trees

Outline:

- Search in secondary storage
- B-Trees
 - properties
 - search
 - insertion

Basic assumption so far: data structures fit completely in main memory (RAM)

- all basic operations have the same cost
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Disk is 10,000–100,000 times slower than RAM

Memory access/transfer	CPU cycles (≈ 1 ns)
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L1 cache	4
L2 cache	10
Local L3 cache	40-75
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CBU evelos ($\sim 1 \text{ pc}$)

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Round trip within a datacenter	500,000
HDD seek	10,000,000
Read 1 MB sequentially from network	10,000,000
Read 1 MB sequentially from disk	30,000,000
Round-trip time USA–Europe	150,000,000

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 DISK-READ(x) reads the object into memory, allowing us to refer to it (and modify it) through x
- Any changes to the object in memory must be eventually saved onto the disk
 DISK-WRITE(x) writes the object onto the disk (if the object was modified)

Assume each node *x* is stored on disk

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ITERATIVE-TREE-SEARCH(T, k)x = T.root1 2 while $x \neq NIL$ 3 DISK-READ(X) **if** *k* == *x*.*key* 4 5 return x 6 elseif k < x. key 7 x = x.left8 else x = x.right9 return x

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cost

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I	$TERATIVE\operatorname{-TREE}\operatorname{-SEARCH}(T,k)$	cost
1	x = T.root	С
2	2 while $x \neq NIL$	С
3	B DISK-READ(X)	100000 <i>c</i>
4	1 if <i>k</i> == <i>x</i> . <i>key</i>	С
5	5 return x	С
6	$\mathbf{b} \qquad \mathbf{elseif} \ k < x. key$	С
7	x = x.left	С
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- Rationale
 - basic in-memory operations are much cheaper
 - the bottleneck is with node accesses, which involve DISK-READ and DISK-WRITE operations

Idea

- In a balanced *binary* tree, *n* keys require a tree of height $h = \lfloor \log_2 n \rfloor$
 - ▶ all the important operations require access to *O*(*h*) nodes
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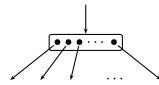
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- In practice we *increase the degree* (or *branching factor*) of each node up to *d* > 2, so *h* = ⌊log_{*d*} *n*⌋
 - ▶ in practice *d* can be as high as a few thousands

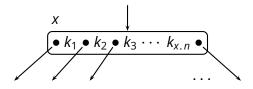
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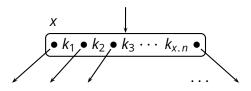
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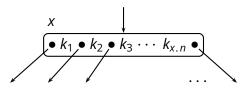


E.g., if d = 1000, then only three accesses (h = 2) cover up to one billion keys



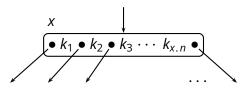


- Every node *x* has the following fields
 - x.n is the number of keys stored at each node



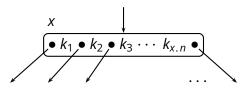
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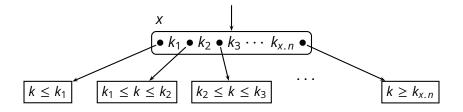
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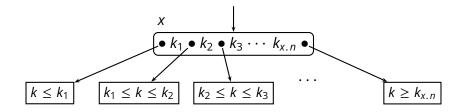
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- *x.leaf* is a Boolean flag that is TRUE if *x* is a *leaf node* or FALSE if *x* is an *internal node*



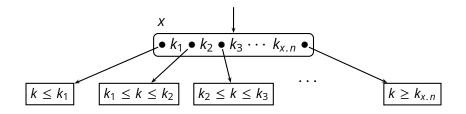
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- x.leaf is a Boolean flag that is TRUE if x is a leaf node or FALSE if x is an internal node
- x.c[1], x.c[2], ..., x.c[x.n + 1] are the x.n + 1 pointers to its children, if x is an *internal node*





■ The keys *x*. *key*[*i*] delimit the ranges of keys stored in each subtree



The keys *x*. *key*[*i*] delimit the ranges of keys stored in each subtree *x*. *c*[1] \rightarrow subtree containing keys $k \le x$. *key*[1] *x*. *c*[2] \rightarrow subtree containing keys *k*, *x*. *key*[1] $\le k \le x$. *key*[2] *x*. *c*[3] \rightarrow subtree containing keys *k*, *x*. *key*[2] $\le k \le x$. *key*[3] ... *x*. *c*[*x*. *n* + 1] \rightarrow subtree containing keys *k*, *k* \ge *x*. *key*[*x*. *n*]

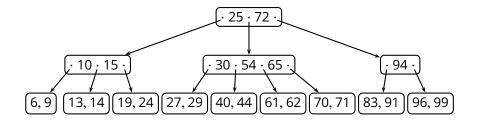
All leaves have the same depth

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• Let $t \ge 2$ be the *minimum degree* of the B-tree

- every node other than the root must have *at least* t 1 *keys*
- every node must contain *at most* 2t 1 *keys*
 - a node is *full* when it contains exactly 2t 1 keys
 - a full node has 2t children

Example



Search in B-Trees

Search in B-Trees

```
B-TREE-SEARCH(x, k)
1 i = 1
2 while i \le x.n and k > x.key[i]
3
        i = i + 1
4 if i \leq x. n and k == x. key [i]
5
        return (x, i)
6
  if x.leaf
7
        return NIL
8
  else DISK-READ(x.c[i])
        return B-TREE-SEARCH(x.c[i], k)
9
```

Theorem: the height of a B-tree containing $n \ge 1$ keys and with a minimum degree $t \ge 2$ is

$$h \leq \log_t \frac{n+1}{2}$$

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- ▶ $n \ge 1$, so the root has at least one key (and therefore two children)
- every other node has at least t children
- ▶ in the worst case, there are two subtrees (of the root) each one containing a total of (n 1)/2 keys, and each one consisting of *t*-degree nodes, with each node containing t 1 keys

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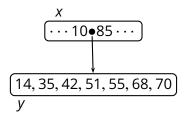
- ▶ $n \ge 1$, so the root has at least one key (and therefore two children)
- every other node has at least t children
- ▶ in the worst case, there are two subtrees (of the root) each one containing a total of (n 1)/2 keys, and each one consisting of *t*-degree nodes, with each node containing t 1 keys
- each subtree contains $1 + t + t^2 \cdots + t^{h-1}$ nodes, each one containing t 1 keys

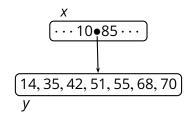
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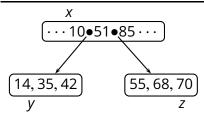
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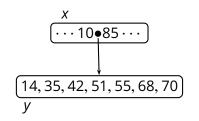
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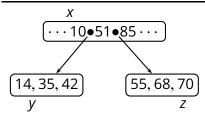
$$n \ge 1 + 2(t^h - 1)$$











B-TREE-SPLIT-CHILD
$$(x, i, y)$$

1 $z = ALLOCATE-NODE()$
2 $z.leaf = y.leaf$
3 $z.n = t - 1$
4 **for** $j = 1$ **to** $t - 1$
5 $z.key[j] = y.key[j + t]$
6 **if not** $y.leaf$
7 **for** $j = 1$ **to** t
8 $z.c[j] = y.c[j + t]$
9 $y.n = t - 1$
10 **for** $j = x.n + 1$ **downto** $i + 1$
11 $x.c[j + 1] = x.c[j]$
12 **for** $j = x.n + 0$ **downto** i
13 $x.key[j + 1] = x.key[j]$
14 $x.key[i] = y.key[t]$
15 $x.n = x.n + 1$
16 **DISK-WRITE** (y)
17 **DISK-WRITE** (z)
18 **DISK-WRITE** (x)

Complexity of **B-TREE-SPLIT-CHILD**

What is the complexity of B-TREE-SPLIT-CHILD?

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- \blacksquare $\Theta(t)$ basic CPU operations
- **3 DISK-WRITE** operations

```
B-TREE-SPLIT-CHILD(x, i, y)
    z = Allocate-Node()
 2 z.leaf = y.leaf
 3 z.n = t - 1
 4 for i = 1 to t - 1
        x.key[j] = x.key[j+t]
 5
 6 if not x.leaf
 7
        for j = 1 to t
 8
             z.c[j] = y.c[j + t]
 9 y.n = t - 1
10 for j = x.n + 1 downto i + 1
11
        x.c[i + 1] = x.c[i]
12 for i = x \cdot n downto i
13
        x.key[i+1] = x.key[i]
14 x.key[i] = y.key[t]
15 x.n = x.n + 1
16 DISK-WRITE(y)
17
    DISK-WRITE(z)
18
    DISK-WRITE(x)
```

Insertion Under Non-Full Node

Insertion Under Non-Full Node

```
B-TREE-INSERT-NONFULL(x, k)
    i = x.n
                                        II assume x is not full
     if x.leaf
 2
 3
          while i \ge 1 and k < x. key[i]
 4
              x.key[i+1] = x.key[i]
 5
              i = i - 1
 6
         x.key[i+1] = k
 7
         x.n = x.n + 1
 8
          DISK-WRITE(x)
 9
     else while i \ge 1 and k < x. key[i]
10
              i = i - 1
11
         i = i + 1
12
          DISK-READ(x.c[i])
13
          if x.c[i].n = 2t - 1 // child x.c[i] is full
14
              B-TREE-SPLIT-CHILD(x, i, x, c[i])
15
               if k > x. key[i]
16
                    i = i + 1
17
          B-TREE-INSERT-NONFULL(x, c[i], k)
```

Insertion Procedure

Insertion Procedure

B-Tree-Insert(T, k)

r = T.root1 2 **if** r.n = 2t - 13 s = Allocate-Node()4 T.root = s5 s.leaf = FALSE 6 s.*n* = 0 7 s.c[1] = r8 **B-TREE-SPLIT-CHILD**(s, 1, r)9 **B-Tree-Insert-Nonfull**(*s*, *k*) **else B-TrEe-INSERTHUL**(*r*, *k*) 10

Insertion Procedure

B-Tree-Insert(T, k)

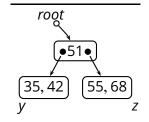
- 1 r = T.root2 **if** r.n = 2t - 1
- 3 s = Allocate-Node()
- 4 T.root = s

5
$$s.leaf = FALSE$$

7
$$s.c[1] = r$$

8 **B-TREE-SPLIT-CHILD**
$$(s, 1, r)$$

- 9 **B-Tree-Insert-Nonfull**(*s*, *k*)
- 10 else B-Tree-Insert-Nonfull(r, k)



■ What is the complexity of **B-TREE-INSERT**?

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- What is the complexity of **B-Tree-Insert**?
- $O(th) = O(t \log_t n)$ basic CPU steps operations
- $O(h) = O(\log_t n)$ disk-access operations
- The best value for *t* can be determined according to
 - the ratio between CPU (RAM) speed and disk-access time
 - the block-size of the disk, which determines the maximum size of an object that can be accessed (read/write) in one shot