

COMP2123 Review Notes

Important: ADT, Time Complexity, Space Complexity, Correctness

Correctness:

- data structures → invariant (the invariant holds before an operation is executed, the operation has the desired result and the invariant still holds after the operation is executed)
- greedy → exchange argument (see 9-Greedy)
- divide and conquer → induction (recursion)

1 - Time Complexity Analysis

We say that $T(n)$ is ... if ...	
constant	$T(n) = \Theta(1)$
logarithmic	$T(n) = \Theta(\log n)$
linear	$T(n) = \Theta(n)$
quasi-linear	$T(n) = \Theta(n \log n)$
quadratic	$T(n) = \Theta(n^2)$
cubic	$T(n) = \Theta(n^3)$
exponential	$T(n) = \Theta(c^n)$

2 - Lists

Data Structure	Operation	Time
Array	<code>get(i)</code> , <code>set(i, e)</code>	$O(1)$
	<code>insert(0, e)</code> , <code>remove(0)</code> from the start	$O(n)$
	<code>insert(i, e)</code> , <code>remove(i)</code> in the middle	$O(n)$
	<code>append(e)</code> , <code>pop()</code> from the end	$O(1)$
	<code>replace(i, e)</code> , <code>size()</code> , <code>isEmpty()</code>	$O(1)$
Singly Linked	<code>get(i)</code>	$O(n)$
/ Doubly Linked	<code>addFirst(e)</code> , <code>removeFirst()</code> from start	$O(1)$
	<code>add(i, e)</code> , <code>remove(i)</code> in middle	$O(n)$
	<code>addLast(e)</code> , <code>removeLast()</code> from end	$O(n) / O(1)$
	<code>replace(i, e)</code>	$O(n)$
	<code>size()</code>	$O(n)$
Stack	<code>push(e)</code> , <code>pop()</code>	$O(1)$
Queue	<code>enqueue(e)</code> , <code>dequeue()</code>	$O(1)$

3 - Trees

Tree ADT

Method	Time
<code>size()</code> , <code>isEmpty()</code>	$O(1)$
<code>root()</code> , <code>parent(p)</code>	$O(1)$
<code>children(p)</code>	$O(c)$
<code>numChildren(p)</code>	$O(1)$
<code>isInternal(p)</code> , <code>isExternal(p)</code> , <code>isRoot(p)</code>	$O(1)$

- Tree Traversals: Preorder, Inorder, Postorder $\rightarrow O(n)$

4 - Binary Search Trees

Binary Search Tree (BST)

1. Properties:

- For any node v , keys in the left subtree are less than v , and keys in the right subtree are greater than v .
- In-order traversal of a BST results in keys in increasing order.

2. Operations:

- **Search:** `search(k, v)` $O(h)$ ($h = \text{height}$)
- **Insertion:** `put(k, o)` $O(h)$
 - If the key exists, replace the value.
 - Otherwise, insert at the reached external node.
- **Deletion:** `remove(k)` $O(h)$
 - **Case 1:** Node has one external child — remove and promote the other child.
 - **Case 2:** Node has two internal children — find the in-order successor, copy its value, and delete it.

3. Complexity:

- **Space:** $O(n)$
- **Best Case Height:** $O(\log n)$
- **Worst Case Height:** $O(n)$

Range Queries in BST

- **Purpose:** Find all keys k in range $k_1 \leq k \leq k_2$.
 - **Algorithm:** in-order (ascending order)
 - Traverse left or right subtree based on key comparisons.
 - $| \text{inside nodes} | \leq | \text{output} |$; $| \text{boundary node} | \leq 2 * \text{tree height}$
 - **Time Complexity:** $O(| \text{output} | + \log n)$
-

AVL Tree (Self-Balancing BST)

nodes usually contains a key/a pointer

1. Properties:

- Balanced BST where the heights of left and right subtrees of every node differ by at most 1.
- **Height:** $O(\log n)$

2. Operations:

- **Search:**
 - **Time Complexity:** $O(\log n)$
- **Insertion:**
 - Standard BST insertion, followed by rebalancing.
 - If balance property is violated, perform rotations
 - **Time Complexity:** $O(\log n)$
- **Deletion:**
 - Standard BST deletion, followed by rebalancing using rotations if necessary.
 - **Time Complexity:** $O(\log n)$

3. Trinode Restructuring:

- Helps restore balance by making the middle node of three unbalanced nodes the root of that subtree.
- **Time Complexity:** $O(1)$ for rotation operations.

Map ADT (Key-Value Store)

Method	Description
<code>size()</code>	Returns the number of entries
<code>isEmpty()</code>	Checks if the map is empty
<code>entrySet()</code>	Returns an iterable of all entries
<code>keySet()</code>	Returns an iterable of all keys

`values()`

Returns an iterable of all values

5 - Priority Queues

Priority queue implementations

Method	Unsorted List	Sorted List	Heap
size, isEmpty	$O(1)$	$O(1)$	$O(1)$
insert	$O(1)$	$O(n)$	$O(\log n)$
min	$O(n)$	$O(1)$	$O(1)$
removeMin	$O(n)$	$O(1)$	$O(\log n)$
remove	$O(1)$	$O(1)$	$O(\log n)$
replaceKey	$O(1)$	$O(n)$	$O(\log n)$
replaceValue	$O(1)$	$O(1)$	$O(1)$

Priority Queue Sorting Algorithms

1. Selection Sort (Unsorted Sequence):

- Time Complexity: `insert` : $O(n)$, `remove_min` : $O(n^2)$

2. Insertion Sort (Sorted Sequence):

- Time Complexity: `insert` : $O(n^2)$, `remove_min` : $O(n)$

3. Heap-Sort (Uses a min-heap for efficient sorting)

- Time Complexity: `insert` , `remove_min` : $O(\log n)$

i	A	s
0	7, 4, 8, 2, 5, 3, 9	3
1	2, 4, 8, 7, 5, 3, 9	5
2	2, 3, 8, 7, 5, 4, 9	5
3	2, 3, 4, 7, 5, 8, 9	4
4	2, 3, 4, 5, 7, 8, 9	4
5	2, 3, 4, 5, 7, 8, 9	5
6	2, 3, 4, 5, 7, 8, 9	6

```
def selection_sort(A):
    n ← size(A)
    for i in [0:n] do
        # find s > i minimizing A[s]
        s ← i
        for j in [i:n] do
            if A[j] < A[s] then
                s ← j
        # swap A[i] and A[s]
        A[i], A[s] ← A[s], A[i]
```

i	A	i
1	7, 4, 8, 2, 5, 3, 9	0
2	4, 7, 8, 2, 5, 3, 9	2
3	4, 7, 8, 2, 5, 3, 9	0
4	2, 4, 7, 8, 5, 3, 9	2
5	2, 4, 5, 7, 8, 3, 9	1
6	2, 3, 4, 5, 7, 8, 2	6

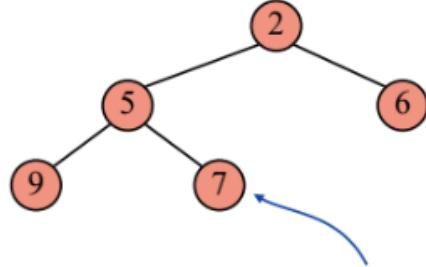
```

def insertion_sort(A):
    n ← size(A)
    for i in [1:n] do
        x ← A[i]
        # move forward entries > x
        j ← i
        while j > 0 and x < A[j-1] do
            A[j] ← A[j-1]
            j ← j - 1
        # if j>0 ⇒ x ≥ A[j-1]
        # if j<i ⇒ x < A[j+1]
        A[j] ← x
    
```

Heap Data Structure (Min-Heap)

- Properties: (remember to explain both nodes and the root of the heap)

1. **Heap-Order:** for every node $m \neq \text{root}$,
 $\text{key}(m) \geq \text{key}(\text{parent}(m))$



2. **Complete Binary Tree:** let h be the height
 - every level $i < h$ is full (i.e., there are 2^i nodes)
 - remaining nodes take leftmost positions of level h

The **last node** is the rightmost node of maximum depth

2. **Height:** $O(\log n)$.

3. **Min-Heap Operations:**

Operation	Description	Time
Build Heap	Builds a heap from an unsorted array	$O(n)$
insert	Insert at the last position and perform upheap	$O(\log n)$
remove_min	Replace the root with the last node, remove the last node, and perform downheap	$O(\log n)$
Access root min	Returns the min/max element without removal	$O(1)$
Decrease/Increase Key	Adjusts the value of a specific key	$O(\log n)$
Find Next Last Node After Deletion	Start from the old last node, go up to find a right child or root, go to sibling, then down to leaf	$O(\log n)$

- **Counting Inversions with Selection Sort:**

- **Inversions** are pairs (i, j) in an array A where $i < j$ but $A[i] > A[j]$.
- By performing **Selection Sort** on an array, the **number of swaps** needed is equal to the **number of inversions** in the array. This is because each swap corrects one inversion, moving a larger element to its proper position relative to a smaller element that was previously after it.

- **Finding the k-th Value in Sorted Order Using Heaps:**

- Given an unsorted array A , you can use a **min-heap** or **max-heap** to efficiently find the k -th smallest or largest element without fully sorting the array.

- **Using a Min-Heap:**

- A **min-heap** helps to track the smallest elements in the array.
- The **root** of the min-heap is the smallest element.
- To find the k -th largest element, keep only the k largest elements in the min-heap by replacing the root if a new element is larger. After inserting k elements, the root will be the k -th largest element.

- **Using a Max-Heap:**

- A **max-heap** works similarly but tracks the largest elements.
- To find the k -th smallest element, maintain a max-heap of size k , where the root is the largest among the k smallest elements seen so far.
- If a new element is smaller than the root, replace the root, ensuring the heap only keeps the smallest k elements. After processing all elements, the root will be the k -th smallest element.

- **Merging k Sorted Lists of Length m Using a Min-Heap:**

- Given k sorted lists, each of length m , the goal is to merge them into a single sorted list efficiently.

- **Method:**

- Use a **min-heap** where each element in the heap represents the smallest unprocessed element from each of the k lists.
- Inserting an element into the min-heap takes $O(\log k)$ time.
- For k lists, inserting and removing elements from the heap will take $O(k \log k)$ time per element added to the result list.

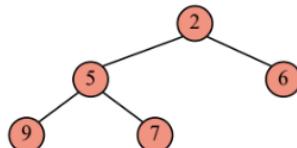
- **Overall Complexity:**

- Since there are m elements in each of the k lists, the total number of elements to merge is km .
- The time complexity for merging all elements is $O(km \log k)$, as each insertion and deletion operation on the min-heap takes $O(\log k)$ time.

Heap Array Representation

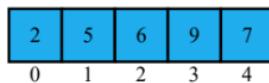
Special nodes:

- root is at 0
- last node is at n-1



For the node at index i:

- the left child is at index $2i+1$
- the right child is at index $2i+2$
- Parent is at index $\lfloor (i-1)/2 \rfloor$



- **Counting Inversions with Selection Sort:**

- the **number of swaps** needed is equal to the **number of inversions** in the array.

- **Finding the k-th Value in Sorted Order Using Heaps:**

- keep only the k largest elements in the min-heap by replacing the root if a new element is larger. After inserting k elements, the root will be the k-th largest element.

- **Merging k Sorted Lists of Length m Using a Min-Heap:**

- For k lists, inserting and removing elements from the heap will take $O(k \log k)$ time per element added to the result list.

Overall Complexity: $O(km \log k)$

6 - Hashing

Key Concepts in Hash Tables

- **Load Factor (α):** Defined as $\alpha = n/N$ (number of elements over table size). Ideally, α should be below 0.75 for optimal performance.

Implementations of Map ADT

Implementation	Description	Insert (put)	Search (get)	Delete (remove)	Space
Simple List-Based Map	Stores items in an unsorted list	$O(1)$ (append)	$O(n)$	$O(n)$	$O(n)$
Array-Based Map	Uses an array for keys in a fixed range (e.g., $[0, N-1]$)	$O(1)$	$O(1)$	$O(1)$	$O(N)$ (for fixed range N)
Hash Table	Maps keys to indices using a hash function	$O(1)$ (average)	$O(1)$ (average)	$O(1)$ (average)	$O(n)$

Collision Handling

Method	Description	Average Time Complexity	Suitable Scenarios
Separate Chaining	Each table cell points to a linked list that holds all items hashed to that index	$O(1+\alpha)$, worst-case $O(n)$	Allows higher load factors; requires extra memory for linked lists
Linear Probing	Places colliding items in the next available position (circularly)	$O(1)$ with low load factor, worst-case $O(n)$ (<code>get</code> , <code>put</code> , <code>remove</code>)	Efficient with careful load factor control, but may cause clustering
Cuckoo Hashing	Uses two hash tables and two hash functions	worse-case $O(1)$ for <code>get</code> , <code>remove</code> , expected $O(1)$ for <code>put</code>	Offers worst-case guarantees for lookups; more complex implementation

Eviction Cycle Detection:

- Use a Counter:** to keep track of the number of evictions. If we evict enough times we are guaranteed to have a cycle.
- Flag Entries:** Keep an additional flag for each entry. Every time we evict an entry, we flag it. After a successful put, we need to unflag the entries flagged.

Set Implementation Using a Map

- Map-Based Set:** Use a map to store elements as keys, ignoring values.
- Performance:** Using a hash-based map, primary set operations (add, remove, contains) typically have $O(1)$ time complexity.
- Using Hash Table with Doubly Linked List for `get`, `put`, `delete` in $O(1)$ Time:**
 - By using a hash table in combination with a doubly linked list, we can perform `get`, `put`, and `delete` operations in constant time, $O(1)$.
 - The doubly linked list maintains a pointer to the elements in the hash table, allowing for efficient insertion and deletion.
 - This approach is commonly used in data structures like **LRU (Least Recently Used) Cache**, where the hash table provides $O(1)$ access to elements, and the doubly linked list maintains the order of elements for quick updates.
- Finding the Most Frequent Value in $O(n)$ Time:**
 - To find the most frequent element in a collection, a hash table can be used to count occurrences.
 - Collision Handling:** To handle hash collisions, linear probing or chaining can be used.

- After constructing the hash table, which stores the frequency of each element, traverse the hash table to identify the element with the highest frequency.
 - This approach runs in $O(n)$ time because inserting and updating counts in the hash table takes $O(1)$ on average per element, and scanning the hash table at the end also takes $O(n)$.
- Using `get()` in a Multimap with $O(1+s)$ Time Complexity:**
 - A **mymap** allows multiple values to be associated with the same key.
 - By implementing a mymap with a hash table, we can retrieve all values associated with a key.
 - Since multiple values may be stored at the same hash address, using `get()` requires retrieving all values associated with that key.
 - The time complexity of `get()` is $O(1+s)$, where s is the number of values associated with the key (i.e., the size of the list at that address). This includes the $O(1)$ time to access the hash bucket and $O(s)$ to retrieve all values.

7 - Graphs

Graph Properties

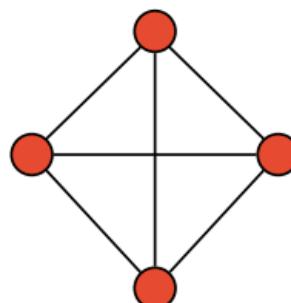
Tree: A connected acyclic graph.

Fact: $\sum_{v \in V} \deg(v) = 2m$

Fact: In a simple undirected graph $m \leq n(n - 1)/2$

Notation

n	number of vertices
m	number of edges
Δ	maximum degree

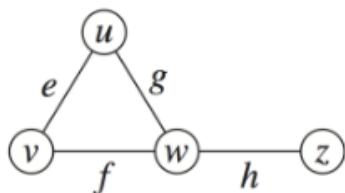


Example: K_4

$$\begin{aligned}n &= 4 \\m &= 6 \\\max \deg &= 3\end{aligned}$$

<ul style="list-style-type: none"> ▪ n vertices, m edges ▪ no parallel edges ▪ no self-loops 	Edge List	Adjacency List	Adjacency Matrix
Space	$O(n + m)$	$O(n + m)$	$O(n^2)$
<code>incidentEdges(v)</code>	$O(m)$	$O(\deg(v))$	$O(n)$
<code>getEdge(u, v)</code>	$O(m)$	$O(\min(\deg(u), \deg(v)))$	$O(1)$
<code>insertVertex(x)</code>	$O(1)$	$O(1)$	$O(n^2)$
<code>insertEdge(u, v, x)</code>	$O(1)$	$O(1)$	$O(1)$
<code>removeVertex(v)</code>	$O(m)$	$O(\deg(v))$	$O(n^2)$
<code>removeEdge(e)</code>	$O(1)$	$O(1)$	$O(1)$

if Adjacency List need traverse, `removeVertex` : $O(n+m)$ `removeEdge` : $O(m)$



	0	1	2	3
$u \rightarrow 0$		e	g	
$v \rightarrow 1$	e		f	
$w \rightarrow 2$	g	f		h
$x \rightarrow 3$			h	

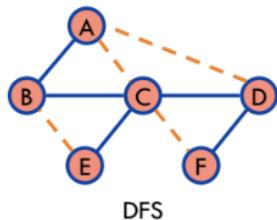
Algorithm	Complexity (Adjacency List)	Edges
DFS	$O(n+m)$	back edges
BFS	$O(n+m)$	cross edges

Applications	DFS	BFS
Spanning forest, connected components, paths, cycles	✓	✓
Shortest paths		✓
Cut edges	✓	

Non-tree DFS edge (v, w)

w is an ancestor of v
in the DFS tree

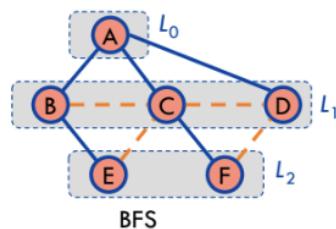
Called back edges



Non-tree BFS edge (v, w)

w is in the same level as v or
in the next level

Called cross edges



Identifying cut edges in $O(n+m)$ time

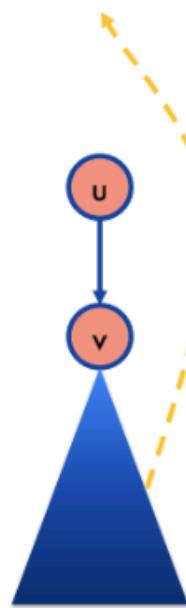
Compute a DFS tree of the input graph $G=(V, E)$

For every u in V , compute $\text{level}[u]$, its level in the DFS tree

For every vertex v compute the highest level that we can reach by taking DFS edges down the tree and then one back edge up. Call this $\text{down_and_up}[v]$

Fact: A DFS edge (u, v) where $u = \text{parent}[v]$ is not a cut edge if and only if $\text{down_and_up}[v] \leq \text{level}[u]$

Basis of an $O(n+m)$ time algorithm for finding cut edges



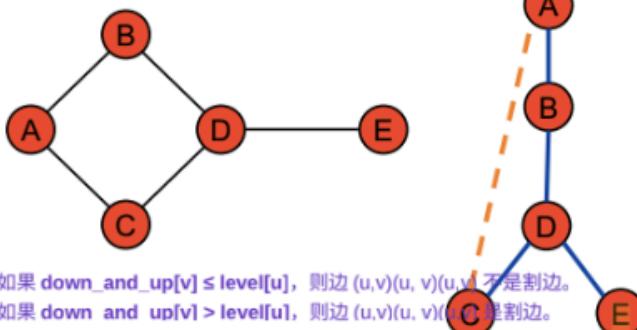
Identifying cut edges in $O(n+m)$ time

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For every vertex v compute the highest level that we can reach by taking DFS edges down the tree and then one back edge up. Call this $\text{down_and_up}[v]$

返祖边 (Back edge) : 连接当前节点和它祖先节点的边 (但不包括直接的父节点)



	level	d&u
A	0	0
B	1	0
C	3	0
D	2	0
E	3	3

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2. Bipartite Check: Using BFS to color each node per layer.

- Bipartite: Adjacent nodes in different layers.

3. Cycle Detection

- Using Adjacency List: $O(n)$
 - Perform DFS to mark each node.
 - If you revisit a marked node, a cycle exists.
- Using Adjacency Matrix: $O(n)$
 - Perform DFS to mark nodes by rows and columns.
 - Check in-degrees and out-degrees to avoid getting stuck.

4. Identifying Cut Vertices and Cut Edges: $O(n+m)$

- Cut Edges (Bridges):
 - In a DFS tree, for an edge (u,v) where u is the parent and v is the child:
 - If $\text{down_and_up}[v] > \text{level}[u]$, (u,v) is a cut edge.
 - If $\text{down_and_up}[v] \leq \text{level}[u]$, (u,v) is not a cut edge.

- **Cut Vertices (Articulation Points):**

- The root of the DFS tree is a cut vertex if it has two or more children.
- For any internal node u with two or more children, u is a cut vertex if and only if $\text{down-and-up}[v] \geq \text{level}(u)$ for any child v .

8 - Graph Algorithms

1. Dijkstra's Algorithm

-
-

2. Shortest Path Problem with Vertex Costs

- Construct a new graph G' based on the original graph G :
 - For each edge (u,v) in G , add an edge (u',v') in G' with weight $\text{weight}(u,v) + \text{cost}(v)$.
- **Binary Heap:**
 - Each insertion is $O(\log n)$.
- **Fibonacci Heap:**
 - Supports $O(1)$ decrease key operations when edge weights are relaxed.

Dijkstra's Algorithm

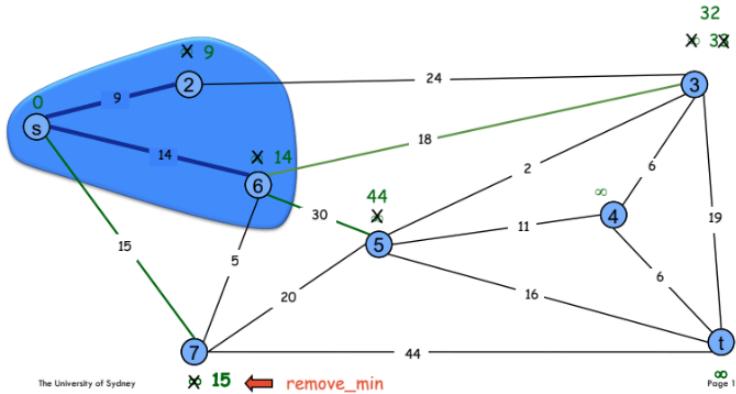
Standard Heap: $O(m\log n)$; Fibonacci Heap: $O(m+n\log n)$; Binary Heap: $O((m+n)\log n)$

- **Algorithm Overview:**

- Initialize the starting node distance as 0, and all other nodes as infinity.
- Update distances of adjacent nodes accordingly while expanding the shortest path.

$$S = \{ s, 2, 6 \}$$

$$PQ = \{ 3, 4, 5, 7, t \}$$



Dijkstra's Algorithm Correctness

Invariant: For each $u \in S = V \setminus Q$, we have $D[u] = \text{dist}_w(s, u)$

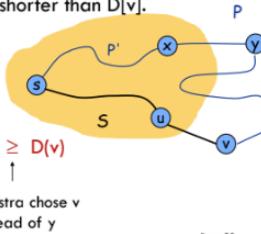
对于每个已经在集合 S 中的顶点 u , 我们已经找到了从起点 s 到该顶点的最短路径距离 $D[u]$

Proof: (by induction on $|S|$) 假设对于已经加入 S 的顶点, 这个不变量成立, 接着证明加入新的顶点后依然保持成立

Base case: $|S| = 1$ is trivial since $D[s] = 0$

Inductive hypothesis: Assume true for $|S| = k \geq 1$.

- Let v be next node added to S and $u = \text{parent}[v]$
- The shortest $s-u$ path plus (u, v) is an $s-v$ path of length $D[v]$
- Consider any $s-v$ path P . We'll see that it's no shorter than $D[v]$.
- Let $x-y$ be the first edge in P that leaves S , and let P' be the subpath to x .
- P is already too long as soon as it leaves S :



$$w(P) \geq w(P') + w(x, y) \geq D(x) + w(x, y) \geq D(y) \geq D(v)$$

inductive hypothesis

Def of $D(y)$

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Dijkstra's Algorithm Correctness

Invariant: The set $\{ (u, \text{parent}[u]) : u \in S \setminus \{ s \} \}$ forms a shortest path tree from s to every node in S

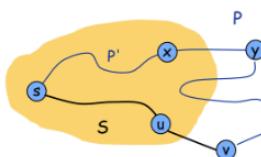
对于已经确定最短路径的节点 (在集合 S 中), 每个节点 u 和它的父节点 $\text{parent}[u]$ 形成了一棵从起点 s 出发的最短路径树

Proof: (by induction on $|S|$)

Base case: $|S| = 1$ is trivial since tree is empty

Inductive hypothesis: Assume true for $|S| = k \geq 1$.

- Let v be next node added to S and $u = \text{parent}[v]$
- $\text{dist}_w(s, v) = \text{dist}_w(s, u) + w[u, v]$
- Adding v to S we still have the invariants



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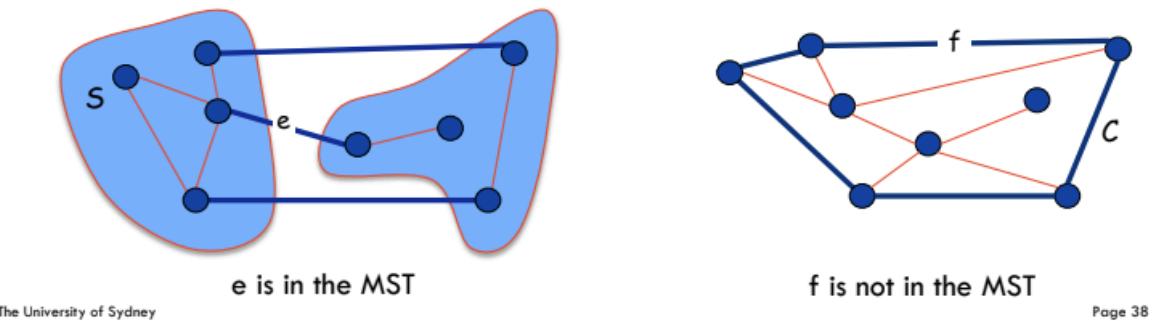
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Minimum Spanning Tree

Simplifying assumption. All edge costs c_e are distinct.

Cut property. Let S be any subset of nodes, and let e be the min cost edge with exactly one endpoint in S . Then the MST contains e .

Cycle property. Let C be any cycle, and let f be the max cost edge belonging to C . Then the MST does not contain f .



Cycle-Cut Intersection

Claim. A cycle and a cutset intersect in an even number of edges.

Prim's Algorithm

- **Steps:**

1. Initialize the MST with an arbitrary vertex.
2. Add the minimum-weight edge connecting the current tree to any vertex not in the tree.
3. Repeat until all vertices are included in the MST.

- **Time Complexity:**

- Binary heap: $O(m\log n)$; Fibonacci heap: $O(m+n\log n)$.

Kruskal's Algorithm

- **Steps:**

1. Sort all edges by weight.
2. For each edge, check if it forms a cycle with the current MST using Union-Find.
3. If no cycle is formed, add the edge to the MST.
4. Stop once $n-1$ edges are added.

- **Time Complexity:**

- Sorting edges: $O(m\log m)$.

- Using Union-Find to check cycles: $O(n^2)$
- `make_sets(A)` : $O(n)$ `find(u)` : $O(1)$ `union(u, v)` : $O(n)$

Union-Find (in Kruskal's Algorithm to detect cycles)

- **Operations:**

1. **make_sets**: Initializes singleton sets for each element.
2. **find**: Finds the root representative of the set containing an element, with path compression to speed up future queries.
3. **union**: Merges two sets, using union by rank to keep the tree shallow.

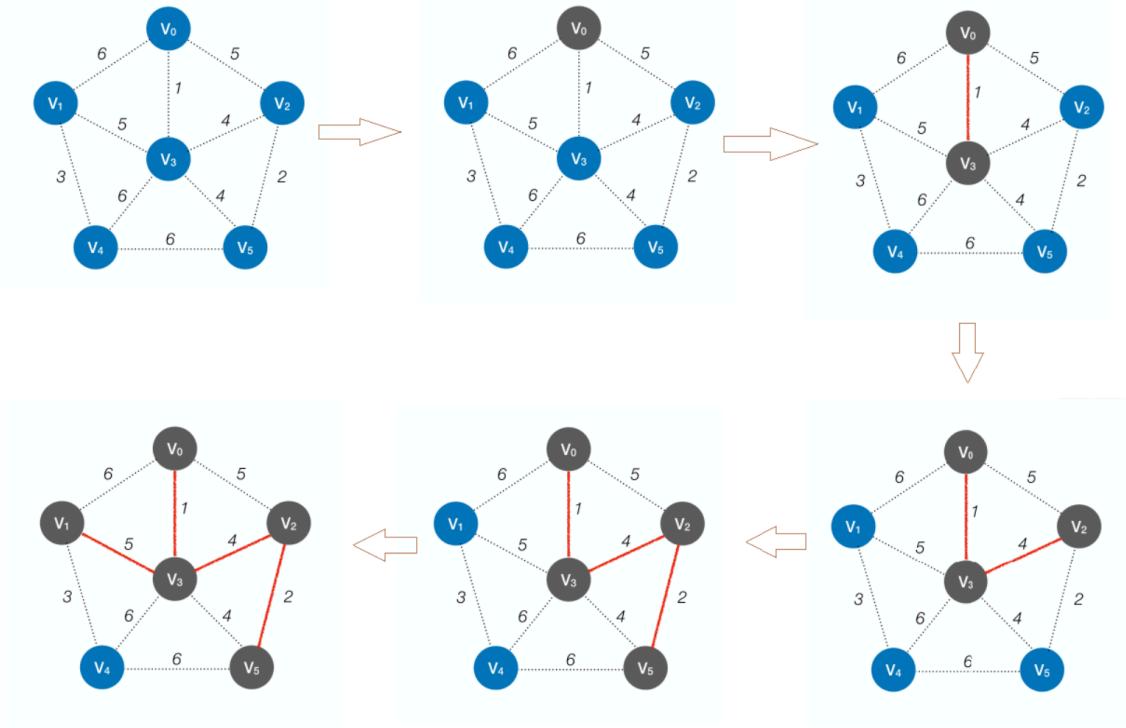
- **Time Complexity:**

- **make_sets**: $O(n)$.
- **find**: $O(\alpha(n))$ with path compression.
- **union**: $O(\alpha(n))$ with union by rank, where $\alpha(n)$ is the inverse Ackermann function (almost constant in practice).

Prim's Algorithm

Time Complexity

- **$O(E \log V)$** using a heap
- **$O(E + V \log V)$** using Fibonacci heap



```

def prim(G, c):
    u ← arbitrary vertex in V
    S ← { u }
    T ← ∅
    while |S| < |V| do
        (u, v) ← min cost edge s.t. u in S and v not in S
        add (u, v) to T
        add v to S
    return T

```

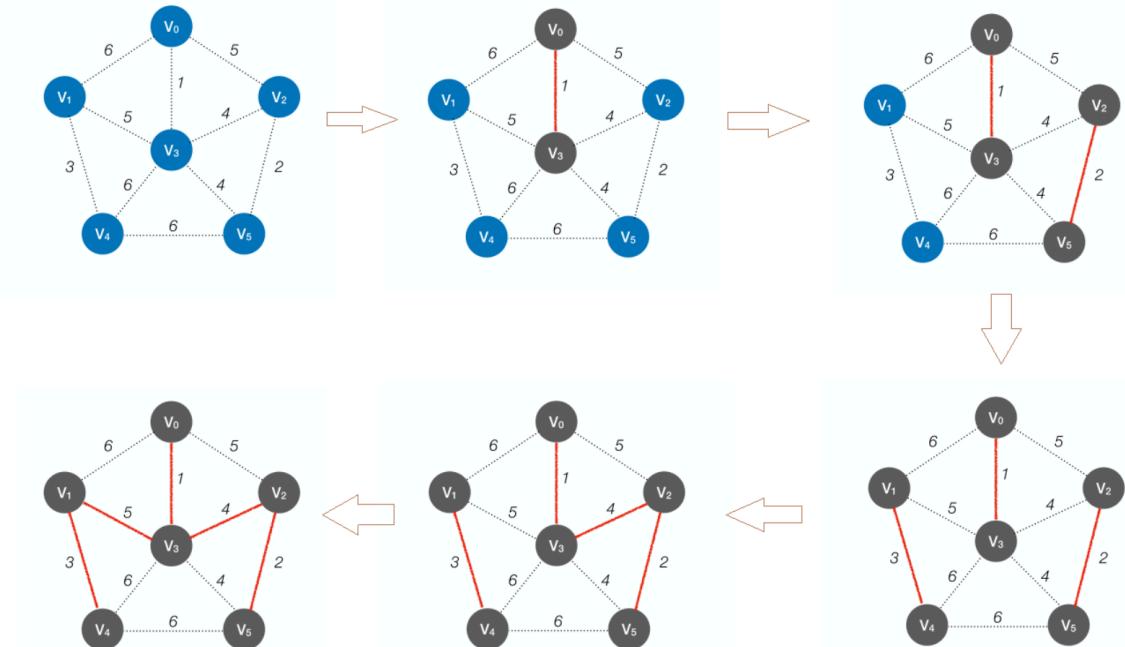
Kruskal's Algorithm

Kruskal's algorithm with a union find implementation

Time Complexity

$O(E \log V) \rightarrow O(E \log E)$ (因为在连通图中，E 最多为 V^2 ,

所以 $\log E$ 和 $\log V$ 的数量级是相同的)。



```

def Kruskal(G,c):

    sort E in increasing c-value
    answer ← [ ]
    comp ← make_sets(V)
    for (u,v) in E do
        if comp.find(u) ≠ comp.find(v) then
            answer.append( (u,v) )
            comp.union(u, v)
    return answer

Union find operations:
• make_sets(A) : one call with |A| = |V|
• find(a) : 2m calls
• union(a,b) : n-1 calls

```

Shortest Path Problem with Edge Weights and Vertex Costs

- Create a new graph G' by modifying each edge (u,v) in G .
- In G' , set the weight of (u',v') to **edge weight + cost of the destination vertex**.
- **Run Dijkstra's Algorithm** on G'

Fibonacci Heap:

- **Decrease Key Operation:** Triggered when an edge weight is relaxed, with complexity $O(m) \times O(1) = O(m)$.
- **Insertion on Vertices:** $O(n\log n)$.
- **Total Complexity with Fibonacci Heap:** $O(m+n\log n)$.

9 -Greedy Algorithms

```

def generic_greedy(input):

    # initialization
    initialize result

    determine order in which to consider input

    # iteratively make greedy choice
    for each element i of the input (in above order) do
        if element i improves result then
            update result with element i

    return result

```

Key Problems and Algorithms

Problem	Greedy Choice	Complexity	Correctness
Fractional Knapsack	Maximize benefit within a weight constraint by taking fractions of items	$O(n\log n)$ for sorting, $O(n)$ for	Optimal (exchange)

		processing	argument)
Interval Partitioning	Minimize the number of classrooms needed for lectures, ensuring no overlap in the same room.	$O(n \log n)$ using a priority queue	Optimal (uses priority queue)
Huffman Encoding	Combine lowest frequency characters	$O(n + d \log d)$, where d is the number of distinct characters	Optimal (builds minimum encoding tree)

Theorem: The greedy strategy of picking item with highest benefit to weight ratio computes an optimal solution.

Proof (sketch):

- Use an exchange argument
- Assume for simplicity that all ratios are different $b_i/w_i \neq b_k/w_k$
- Consider some feasible solution x different than the greedy one
- There must be items i and k s.t. $x_i < w_i$, $x_k > 0$ and $b_i/w_i > b_k/w_k$
- If we replace some k with some of i , we get a better solution
- How much? $\min\{w_i - x_i, x_k\}$
- Thus, there is no better solution than the greedy one

Thm: Huffman's algorithm computes a minimum length encoding tree of (C, f)

Proof (by induction):

- If $|C| = 1$ then the encoding is trivially optimal
- If $|C| > 1$ then let (C', f') be the contracted instance
- By inductive hypothesis, the encoding tree T' constructed for (C', f') is optimal
- Recall that

$$\sum_{c \text{ in } C} f(c) * \text{depth}_T(c) = \sum_{c \text{ in } C'} f'(c) * \text{depth}_{T'}(c) + f(i) + f(k)$$

thus, the tree T is optimal for (C, f)

Summary of Concepts

1. Optimal Solution in an Algorithm:

- The algorithm always returns an **optimal solution**.

- It does not always find the minimum difference between two values; instead, it finds the **minimum for each element**.
- This ensures the overall minimum in the difference as well.

2. Tree Construction with Frequencies $f=2^i$ if $f=2^i$

- When given frequencies in the form $f=2^i$, the algorithm constructs a tree where **every internal node has an external node**.

$$f=2^i \text{ if } f=2^i$$

- The algorithm creates a new node and picks the smallest frequency, corresponding to the leaf (external node).
- Every internal node will always have an external frequency 2^i .

$$2^i 2^i$$

3. Determining Interval Length in a Set:

- To find the interval covering all points in a set, **sort** the points first.
- For each point, check if it has been covered.
- If not covered, start from that point and expand the interval to cover other points.
- **Time Complexity:** $O(n\log n)$ due to sorting.

4. Optimal Job Scheduling:

- To get the optimal schedule, **sort jobs** by the ratio of **job weight to time**.
- Compute the **ratio of job weight to time** for prioritization.
- This returns the optimal schedule that maximizes the total weight.
- **Time Complexity:** $O(n\log n)$, as sorting is required.

10 - Divide and Conquer I

- **Divide:** If it's a base case (like a problem of size 1), solve directly; otherwise, split the problem into sub-problems.
- **Recur/Delegate:** Recursively solve each sub-problem.
- **Conquer:** Combine the solutions of the sub-problems to form the overall solution.

Complexity Analysis via Recurrence Relations

Example Algorithm	Recurrence	Solution	Correctness
Array Binary Search	$T(n)=T(n/2)+O(1)$	$O(\log n)$	Invariant (x is in A)
Merge Sort	$T(n)=2T(n/2)+O(n)$	$O(n\log n)$	Induction
Quick Sort	$T(n)=T(nL)+T(nR)+O(n)$	$O(n\log n)$ on average	

Binary search correctness

Invariant: If x is in A before the divide step, then x is in A after the divide step

- if $A[\lfloor n/2 \rfloor] > x$, then x must be $A[0 \text{ to } \lfloor n/2 \rfloor - 1]$
- if $A[\lfloor n/2 \rfloor] < x$, then x must be in $A[\lfloor n/2 \rfloor + 1 \text{ to } n - 1]$

Every divide step leads to a smaller array.

Thus, if x in A , we will eventually inspect its position due to the invariant and return "Yes".

Thus, if x is not in A , then eventually we reach the empty array and return "No".

Merge: Correctness

Induction hypothesis:

- After the i -th iteration, our result contains the i smallest elements in sorted order

Base case:

- After 0 iterations, our result is empty, so it contains the 0 smallest elements in sorted order

Induction:

- Assume IH after iteration k , to prove it after iteration $k+1$
- Since both halves are sorted and we add the smallest element not already in result, result now contains the $k+1$ smallest elements
- Sorted order follows from the fact that both halves are sorted, thus adding the smallest element implies sorted order of result

Merge-Sort: Correctness

Induction hypothesis:

- Merge-Sort correctly sorts an array of size i

Base case:

- If our array has size 0 or 1, it's already sorted

Induction:

- Assume IH for all arrays up to size k , to prove it for array of size $k+1$
- Splitting the array in half gives us two array of size at most k , so by IH those are sorted correctly
- We proved that given two sorted arrays, Merge returns a correctly sorted array containing the elements of both arrays
- Hence, by running Merge on the two sorted halves, we sort the original array

Quick sort

1. **Divide** Choose a random element from the list as the **pivot**

Partition the elements into 3 lists:

(i) less than, (ii) equal to and (iii) greater than the pivot

2. **Recur** Recursively sort the less than and greater than lists

3. **Conquer** Join the sorted 3 lists together



Proof by Unrolling - $T(n)=2T(n/2) + O(n)$

Hence, the recursion is:

$$T(n) = \begin{cases} T(n) = 2T(n/2) + O(n) & \text{for } n > 1 \\ O(1) & \text{for } n = 1 \end{cases}$$

which solves to

$$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + O(n) = c \cdot n + 2 \cdot c \cdot \frac{n}{2} + 4 \cdot c \cdot \frac{n}{4} + \dots = O(n \log n)$$

Simplifying the Series: The recursive term $T\left(\frac{n}{2^k}\right)$ reaches the base case when $\frac{n}{2^k} = 1$, which implies $k = \log_2(n)$. Substituting $k = \log_2(n)$ gives:

$$T(n) = n \cdot T(1) + c \cdot n \left(1 + \frac{1}{2} + \frac{1}{4} + \dots + \frac{1}{n}\right)$$

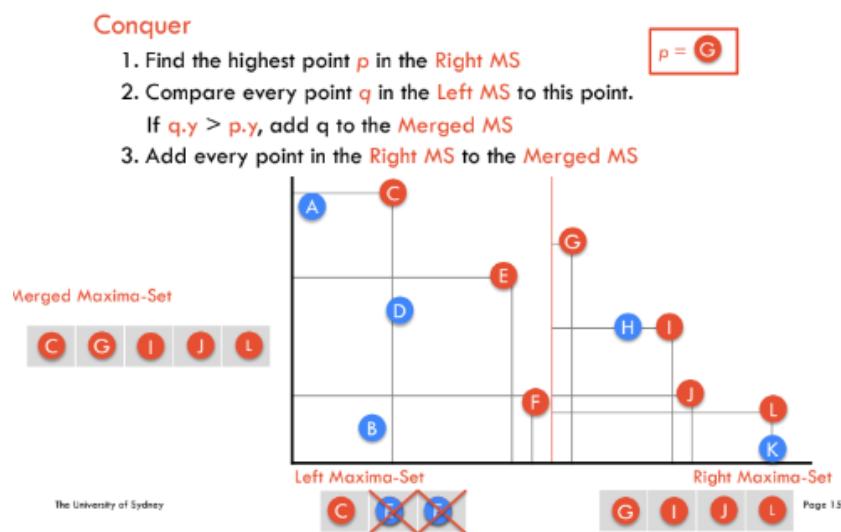
Some recurrence formulas with solutions

Recurrence	Solution
$T(n) = 2 T(n/2) + O(n)$	$T(n) = O(n \log n)$
$T(n) = 2 T(n/2) + O(\log n)$	$T(n) = O(n)$
$T(n) = 2 T(n/2) + O(1)$	$T(n) = O(n)$
$T(n) = T(n/2) + O(n)$	$T(n) = O(n)$
$T(n) = T(n/2) + O(1)$	$T(n) = O(\log n)$
$T(n) = T(n-1) + O(n)$	$T(n) = O(n^2)$
$T(n) = T(n-1) + O(1)$	$T(n) = O(n)$

11 - Divide and Conquer II

Maxima-Set (Pareto Frontier)

1. **Preprocessing:** Sort points by x-coordinate (and y-coordinate to break ties).
2. **Divide:** Split into two halves.
3. **Recur:** Find maxima for each half.
4. **Conquer:** Combine results by comparing points on the left to the highest point on the right.
 - **Time Complexity:** $O(n \log n)$ due to sorting and merging.



Integer Multiplication

Let $x = x_1 2^{n/2} + x_0$ and $y = y_1 2^{n/2} + y_0$

$$\begin{aligned}x \cdot y &= x_1 y_1 2^n + (x_1 y_0 + x_0 y_1) 2^{n/2} + x_0 y_0 \\(x_1 + x_0)(y_1 + y_0) &= x_1 y_1 + x_1 y_0 + x_0 y_1 + x_0 y_0\end{aligned}$$

We can compute the product of two n -digit numbers by making 3 recursive calls on $n/2$ -digit numbers and then combining the solutions to the subproblems.

Divide step (produce halves) takes $O(n)$

Recur step (solve subproblems) takes $3 T(n/2)$

Conquer step (add up results) takes $O(n)$

$$T(n) = \begin{cases} 3 T(n/2) + O(n) & \text{for } n > 1 \\ O(1) & \text{for } n = 1 \end{cases}$$

This solves to $T(n) = O(n^{\log_2 3})$, where $\log_2 3 \approx 1.6$
Better than naïve!!!

Selection (Median of Medians)

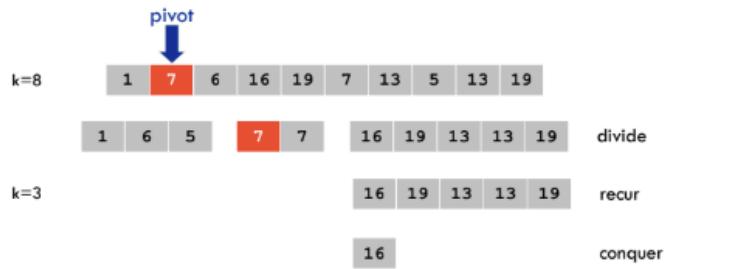
1. **Divide** Choose a random element from the list as the **pivot**

Partition the elements into 3 lists:

(i) less than, (ii) equal to and (iii) greater than the pivot

2. **Recur** Recursively select right element from correct list

3. **Conquer** Return solution to recursive problem



The University of Sydney

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Master Theorem

先看主定理的内容：

设某个递归算法的时间复杂度递归公式为： $T(n) = a * T(\frac{n}{b}) + n^d$, 其中 $a > 1, b > 1, d > 0$ 。则有：

Master Theorem

- 当 $a < b^d$, 也就是 $\log_b a < d$ 时, $T(n) = O(n^d)$
- 当 $a = b^d$, 也就是 $\log_b a = d$ 时, $T(n) = O(n^{\log_b a} * \log n)$
- 当 $a > b^d$, 也就是 $\log_b a > d$ 时, $T(n) = O(n^{\log_b a})$

Let $f(n)$ and $T(n)$ be defined as follows:

$$T(n) = \begin{cases} a T(n/b) + f(n) & \text{for } n \geq d \\ c & \text{for } n < d \end{cases}$$

Depending on a, b and $f(n)$ the recurrence solves to:

1. if $f(n) = O(n^{\log_b a - \varepsilon})$ for $\varepsilon > 0$ then $T(n) = \Theta(n^{\log_b a})$,
2. if $f(n) = \Theta(n^{\log_b a} \log^k n)$ for $k \geq 0$ then $T(n) = \Theta(n^{\log_b a} \log^{k+1} n)$,
3. if $f(n) = \Omega(n^{\log_b a + \varepsilon})$ and $a f(n/b) \leq \delta f(n)$ for $\varepsilon > 0$ and $\delta < 1$ then $T(n) = \Theta(f(n))$,

Note: If $f(n)$ is given as big-O, you can only conclude $T(n)$ as big-O (not Θ).

Note: You should be able to solve all recurrences in this class using unrolling, but if you are comfortable using the Master Theorem, go for it.