

UNIT -2

Greedy Method in Algorithm Design – Detailed Explanation

Overview

The **Greedy Method** is an algorithmic paradigm used for solving optimization problems. It builds up a solution **piece by piece**, always choosing the **next piece** that offers the **most immediate benefit** (i.e., the "greedy" choice), **without considering the global consequences**.

It does not always produce the optimal solution for all problems, but for **some problems**, it does lead to the **globally optimal** solution.

Key Characteristics of Greedy Algorithms

1. **Greedy Choice Property:** A global optimum can be arrived at by selecting a local optimum.
2. **Optimal Substructure:** A problem has an optimal substructure if an optimal solution can be constructed from optimal solutions of its subproblems.

If a problem has both properties, a greedy algorithm is often an appropriate solution.

General Approach of Greedy Method:

1. **Start** with an empty solution.
2. **Repeat:**
 - Choose the best option **based on a local decision** (e.g., max profit, min weight, etc.).
 - Add it to the solution.
3. **Stop** when you reach the goal or no more choices are possible.

4. **Return** the solution.

General Structure of a Greedy Algorithm

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1. Initialize a solution set (often empty).
 2. While the solution is not complete:
 - a. Choose the best possible option based on the current state (greedy choice).
 - b. Add this choice to the solution set.
 - c. Update the state.
 3. Return the solution set.
-
-

Greedy vs Dynamic Programming

Feature	Greedy Method	Dynamic Programming
Decision Making	Local optimal choice	Optimal choice based on subproblems
Solution Guarantee	Not always optimal	Always optimal (for problems with optimal substructure)
Time Complexity	Often faster	Generally more time-consuming
Space Complexity	Low	Higher due to memoization

When Not to Use Greedy Algorithms

- When the problem **lacks optimal substructure**.
- When the **local optimum** choice leads to a **globally suboptimal** solution.

- Example: **0/1 Knapsack Problem** – Greedy fails to give optimal result.
-

Simple Example: Coin Change Problem (Greedy Version)

Problem:

You need to make change for ₹30 using the minimum number of coins.

Available coins: ₹1, ₹2, ₹5, ₹10

Greedy Strategy:

Always take the highest denomination coin that doesn't exceed the remaining amount.

Step-by-step Solution:

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Remaining Amount = 30

- Take ₹10 → Remaining = 20

- Take ₹10 → Remaining = 10

- Take ₹10 → Remaining = 0

Coins used: [10, 10, 10]

Minimum number of coins = 3

Advantages of Greedy Algorithms

- Simple to design and implement.
- Generally efficient and fast.
- Uses less memory compared to dynamic programming.

✖ Disadvantages

- Doesn't always give the optimal solution.
- Not suitable for all problem types.

📘 Definition of Fractional Knapsack Problem

The **Fractional Knapsack Problem** is an optimization problem in which you are given a set of items, each with a **value** and a **weight**, and a knapsack with a **maximum weight capacity**.

The goal is to **maximize the total value** in the knapsack by selecting items. Unlike the 0/1 Knapsack problem, you **can take fractions of an item** rather than having to take it entirely or not at all.

🔑 Key Point:

You are **allowed to break items** and take only a part of them to fill the knapsack optimally.

🧠 Example:

If an item has:

- Value = ₹100
- Weight = 10 kg
And the knapsack has only 5 kg space left,
You can take **half** of the item, gaining **₹50** in value.

✅ Problem Statement

You are given:

- A knapsack with capacity W
- n items, each with:

- $\text{value}[i]$ – value of item i
 - $\text{weight}[i]$ – weight of item i
 - ◆ **Goal:** Maximize total value placed into the knapsack.
 - ◆ **Condition:** You **can take fractions** of items (unlike the 0/1 knapsack).
-

Greedy Approach

The greedy strategy:

1. Calculate **value per unit weight** (value/weight) for each item.
 2. Sort items by this ratio in **descending order**.
 3. Pick items in this order:
 - If the entire item fits, take it.
 - If not, take the **fraction that fits**.
-

Algorithm Steps

Step-by-step procedure:

1. Calculate value/weight ratio for all items.
2. Sort items based on this ratio in descending order.
3. Initialize $\text{total_value} = 0$ and $\text{remaining_capacity} = W$.
4. For each item:
 - If $\text{item weight} \leq \text{remaining capacity}$:
 - Take the full item
 - Add its value to total_value
 - Subtract weight from $\text{remaining_capacity}$
 - Else:
 - Take the fractional part that fits
 - Add corresponding value

- Break (knapsack is full)

5. Return total_value.

Algorithm (Pseudo-Code)

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```
function fractionalKnapsack(W, items):  
    for each item:  
        compute value_per_weight = value / weight  
  
    sort items by value_per_weight in descending order  
  
    total_value = 0  
  
    for item in sorted_items:  
        if item.weight ≤ W:  
            W = W - item.weight  
            total_value += item.value  
        else:  
            fraction = W / item.weight  
            total_value += item.value * fraction  
            break // knapsack is full  
  
    return total_value
```

Example

Let:

- Capacity $W = 50$
- Items:

Item Value Weight Value/Weight

A 60 10 6.0

B 100 20 5.0

C 120 30 4.0

Sorted Order:

$A > B > C$

Fill Knapsack:

- Take A (10) \rightarrow Remaining = 40 \rightarrow Value = 60
- Take B (20) \rightarrow Remaining = 20 \rightarrow Value = 160
- Take 20/30 of C \rightarrow Value = $120 \times (20/30) = 80$

✓ **Total Value = 60 + 100 + 80 = 240**

✓ Advantages

Feature	Description
♦ Simplicity	Easy to understand and implement
♦ Fast	Efficient with time complexity $O(n \log n)$ (due to sorting)
♦ Optimal Result	Always gives optimal result for fractional version
♦ Useful in real life	Applies to problems like cutting, packing, budgeting

✗ Disadvantages

Limitation	Explanation
✗ Doesn't work for 0/1 knapsack	Greedy may miss better combinations
✗ Assumes divisibility	Not all items in real-life can be split (e.g., laptop)
✗ May be misleading	For certain coin or resource problems, greedy fails

🕒 Time Complexity

- Sorting items by ratio: $O(n \log n)$
 - Iterating through items: $O(n)$
 - ✓ **Total Time Complexity: $O(n \log n)$**
 - ✓ **Space Complexity: $O(1)$** (or $O(n)$ if storing additional data)
-

📌 Use Cases

- Budget planning with divisible resources
 - Resource allocation (e.g., allocating computing power)
 - Industrial cutting or material use where splitting is allowed
 - Bandwidth allocation problems
-

✓ Summary

Aspect	Detail
Problem Type	Optimization
Strategy	Greedy – pick based on value/weight
Can take fractions?	✓ Yes
Optimal solution?	✓ Yes for fractional, ✗ No for 0/1 version
Time Complexity	$O(n \log n)$

Would you like a **Python, C++, or Java implementation**, or a **visual diagram** for this example?

You said:

defination

ChatGPT said:

🌟 Job Sequencing with Deadlines

✅ Definition

The **Job Sequencing with Deadlines** problem is an optimization problem where:

- You are given a list of **jobs**.
- Each job has a **deadline** and a **profit**.
- Each job takes **one unit of time** to complete.
- **Only one job can be done at a time.**

Your goal is to **schedule jobs** in such a way that the **total profit is maximized** and **no job is scheduled after its deadline**.

💡 Approach (Greedy Algorithm)

The Greedy approach schedules the **most profitable jobs first**, ensuring they are done **before their deadlines**, if possible.

🔄 Steps:

1. **Sort** all jobs in **descending order of profit**.
2. Create a time slot array of size = max deadline.
3. For each job:
 - Try to place it in the latest **available time slot \leq its deadline**.
 - If a slot is found, schedule the job.
4. Repeat until all jobs are checked or all slots are filled.

📌 Algorithm (Pseudocode)

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```
function jobSequencing(jobs):  
    sort jobs by descending profit  
    maxDeadline = max(jobs.deadline)  
    slots = array of size maxDeadline, initialized to None  
  
    for job in jobs:  
        for j in range(min(job.deadline, maxDeadline) - 1, -1, -1):  
            if slots[j] is None:  
                slots[j] = job  
                break  
  
    return slots, total profit
```

✅ Advantages

Advantage	Description
⚙️ Fast and efficient	$O(n \log n)$ due to sorting
🧠 Simple logic	Easy to implement using greedy
💰 Maximizes profit	Selects best jobs based on returns
📦 Good for scheduling	Used in OS task scheduling, manufacturing

❌ Disadvantages

Disadvantage	Explanation
✗ Assumes unit job time	Doesn't handle variable-duration jobs
✗ Needs sorting	Sorting overhead for large inputs
✗ Not always optimal	For jobs with dependencies or setup times
✗ Deadlines must be known	Can't work in real-time dynamic scenarios

Real-Life Applications

- Job/task scheduling in operating systems
 - Manufacturing & assembly line optimization
 - CPU time slot allocation
 - Advertising slot scheduling
-

Summary

Feature	Description
Problem Type	Greedy – maximize profit with constraints
Time Complexity	$O(n \log n + n \times d)$ where $d = \max \text{deadline}$
Output	Job order that gives maximum profit
Input Assumption	Jobs take 1 unit time and no overlap

Let me know if you want the **code implementation** in a specific language, a **flowchart**, or more **practice questions**!

You said:

question $n=4$, $[p_1, p_2, p_3, p_4] = [70, 12, 18, 35]$ and $[d_1, d_2, d_3, d_4] = [2, 1, 2, 1]$

ChatGPT said:

Let's solve the **Job Sequencing with Deadlines** problem using the given values:

 **Given:**

- **Number of Jobs, $n = 4$**
- **Profits = [70, 12, 18, 35]**
- **Deadlines = [2, 1, 2, 1]**

We can denote the jobs as:

Job Profit (P) Deadline (D)

J1 70 2

J2 12 1

J3 18 2

J4 35 1

 **Step 1: Sort Jobs by Profit (Descending)**

Sorted list:

Job Profit Deadline

J1 70 2

J4 35 1

J3 18 2

J2 12 1

 **Step 2: Initialize Time Slots**

- **Max deadline = 2**
- **Create slots = [None, None] → represents slot 1 and slot 2**

✅ **Step 3: Assign Jobs to Latest Possible Slot \leq Deadline**

♦ **Try J1 (Profit 70, Deadline 2):**

- Slot 2 is free \rightarrow assign J1 to slot 2
➡ slots = [None, J1]

♦ **Try J4 (Profit 35, Deadline 1):**

- Slot 1 is free \rightarrow assign J4 to slot 1
➡ slots = [J4, J1]

♦ **Try J3 (Profit 18, Deadline 2):**

- Slot 2 is taken \rightarrow check slot 1 \rightarrow also taken
➡ Cannot schedule J3

♦ **Try J2 (Profit 12, Deadline 1):**

- Slot 1 is taken
➡ Cannot schedule J2

🔍 **Result**

- **Scheduled Jobs:** J4, J1 (at slot 1 and 2)
- **Total Profit:** $35 + 70 = ₹105$

✅ **Final Job Schedule:**

Slot Job Profit

1 J4 35

2 J1 70

Minimum-Cost Spanning Tree (MST)

✔ Definition:

A **Minimum-Cost Spanning Tree (MST)** is a subset of the edges of a **connected, undirected, weighted graph** that:

- Connects **all the vertices** together,
 - **Has no cycles** (i.e., it's a tree),
 - And has the **minimum possible total edge weight** among all such spanning trees.
-

💡 Key Properties of an MST:

- Includes **all vertices** (V) in the graph.
 - Contains **$V - 1$ edges** (no cycles).
 - Total edge weight is **minimized**.
 - There may be **multiple MSTs** if weights allow ties.
-

Why MST is Important (Applications)

- Network design (e.g., wiring, computer networks, roads).
 - Reducing cost in connecting all components.
 - Clustering data in machine learning.
 - Image processing (e.g., segmentation).
-

Two Main MST Algorithms:

Algorithm Basis		Best for
Prim's	Grow a single tree	Dense graphs
Kruskal's	Build forest, then merge	Sparse graphs

Prim's Algorithm (Greedy Tree Expansion)

Definition

Prim's Algorithm is a **greedy algorithm** used to find the **Minimum Spanning Tree (MST)** of a **connected, undirected, weighted graph** by **growing the MST one vertex at a time**, always choosing the **minimum weight edge** that connects a visited node to an unvisited node.

Key Idea

- Start from any vertex.
 - Repeatedly add the **cheapest edge** connecting the tree to a vertex not in the tree.
 - Continue until **all vertices** are included in the MST.
-

Step-by-Step Approach

1. Initialize:

- Start from any arbitrary vertex.
- Mark it as visited.
- Use a **min-heap** (priority queue) to keep track of the **cheapest edge** to an unvisited vertex.

2. Loop:

- Pick the **minimum-weight edge** from the heap that connects to an unvisited vertex.
 - Add that vertex to the MST.
 - Mark it as visited.
 - Add all its outgoing edges (to unvisited vertices) to the heap.
 - Repeat until all vertices are included.
-

Data Structures Used:

Structure	Purpose
Min-Heap / Priority Queue	To efficiently select the next minimum edge
Visited Array	To track which nodes are already in MST
Adjacency List	To represent the graph efficiently

Time Complexity

Version	Time Complexity
Naive (adj. matrix)	$O(V^2)$
With Min-Heap & List	$O(E \log V)$

Example

Graph:

mathematica

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Vertices: A, B, C, D

Edges:

A-B (1)

A-C (3)

B-C (1)

B-D (6)

C-D (4)

Execution (Start from A):

1. A is added to MST
2. Add edges A-B(1), A-C(3) to heap → pick A-B
3. Add B to MST

4. Add B-C(1), B-D(6) to heap → pick B-C
5. Add C to MST
6. Add C-D(4) → pick it
7. Add D to MST

✅ **Final MST Edges:**

- A-B (1), B-C (1), C-D (4)
 - **Total Cost = 6**
-

🔧 **Prim's Algorithm - Pseudocode**

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function PrimMST(graph):

 Initialize: visited = [False] * n

 minHeap = []

 MST = []

 Add (0, source_node) to minHeap

 while minHeap is not empty:

 (weight, u) = minHeap.pop()

 if u is already visited:

 continue

 mark u as visited

 add edge to MST

for all neighbors v of u :

if v not visited:

push ($\text{weight}(u, v), v$) to minHeap

return MST

✓ Advantages of Prim's Algorithm

Advantage	Description
✓ Efficient on dense graphs	Because it avoids sorting all edges
✓ Builds tree incrementally	Easy to track and control growth
✓ Deterministic result	Produces consistent MST with same start

✗ Disadvantages

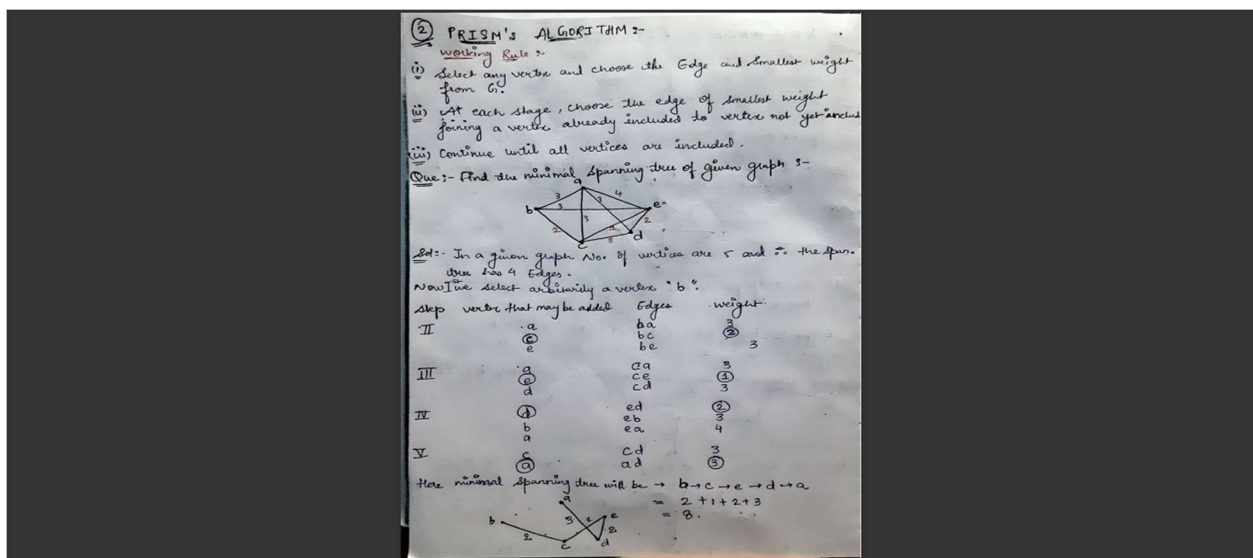
Disadvantage	Explanation
✗ Needs extra data structures	Requires priority queue & visited tracking
✗ Slower on sparse graphs	Compared to Kruskal in some cases
✗ Only for connected graphs	Doesn't handle disconnected graphs

■ Use Cases

- Designing least-cost communication networks
- Laying cables and pipes efficiently
- Road or electrical wiring planning
- Image segmentation

Summary

Feature	Description
Algorithm Type	Greedy
Graph Type	Undirected, connected, weighted
Data Structures Used	Min-heap (priority queue), visited array
Time Complexity	$O(E \log V)$ with binary heap
Output	Minimum-cost spanning tree



② PRISM'S ALGORITHM:-

Working Rule:-

- Select any vertex and choose the edge of smallest weight from it.
- At each stage, choose the edge of smallest weight joining a vertex already included to a vertex not yet included.
- Continue until all vertices are included.

Ques:- Find the minimum spanning tree of given graph:-

Sol:- In a given graph No. of vertices are 5 and 8 edges. Thus 4 edges.

Now I'll select arbitrarily a vertex "a".

Step	Vertex that may be added	Edges	Weight
I	a		
II	b	ab, bc, bd	2, 3, 4
III	c	ca, cb, cd, ce	3, 3, 3, 4
IV	d	ed, eb, ea, da	5, 4, 5, 4
V	e	ed, ea, ad	5, 5, 4

Here minimum spanning tree will be $a \rightarrow b \rightarrow c \rightarrow d \rightarrow e$

$= 2 + 3 + 3 + 5$
 $= 13$

Definition

Kruskal's Algorithm is a **greedy algorithm** used to find the **Minimum Spanning Tree (MST)** of a **connected, undirected, weighted graph** by **selecting the lowest-weight edges first** and ensuring that no cycles are formed.

Key Idea

- Sort all edges in **increasing order of weight**.
 - Use a **Disjoint Set (Union-Find)** data structure to check for cycles.
 - Repeatedly add the **smallest edge** that doesn't form a cycle until MST is complete.
-

Concept: Spanning Tree

A **spanning tree**:

- Connects all vertices.
 - Has no cycles.
 - Has exactly $V - 1$ edges for V vertices.
-

Step-by-Step Approach

1. Sort all edges in non-decreasing order by weight.

2. Initialize:

- Each vertex is its own **disjoint set** (component).
- Create an empty list for MST.

3. Iterate over sorted edges:

- For each edge (u, v) :
 - If u and v belong to **different sets** (no cycle), add edge to MST.
 - Merge the sets using **Union-Find**.

4. Repeat until MST contains $V - 1$ edges.

Time Complexity

Step	Complexity
Sorting edges	$O(E \log E)$

Step	Complexity
Union-Find operations $O(E \log V)$ (with path compression + union by rank)	
Overall	$O(E \log V)$

Data Structures Used

Structure	Purpose
Edge List	To sort and iterate edges by weight
Union-Find (DSU)	To detect cycles efficiently
MST Edge List	To store result edges

Example

Graph:

mathematica

Copy code

Vertices: A, B, C, D

Edges:

A-B (1)

A-C (3)

B-C (1)

B-D (6)

C-D (4)

Step 1: Sort edges

Sorted by weight:

- A-B (1)
- B-C (1)

- A-C (3)
- C-D (4)
- B-D (6)

✓ Step 2: Initialize DSU

✓ Step 3: Add edges to MST

- A-B → ✓ (no cycle)
- B-C → ✓ (no cycle)
- A-C → ✗ (would form cycle)
- C-D → ✓ (no cycle)
- B-D → ✗ (already connected)

✓ Final MST:

- Edges: A-B (1), B-C (1), C-D (4)
- **Total cost: 6**

Pseudocode of Kruskal's Algorithm

plaintext

Copy code

```
function KruskalMST(graph):
```

```
    result = []
```

```
    sort all edges in increasing weight
```

```
    create disjoint sets for all vertices
```

```
    for each edge (u, v) in sorted edge list:
```

```
        if find(u) ≠ find(v):
```

```
            add edge to result
```

union(u, v)

return result

✅ Advantages of Kruskal's Algorithm

Advantage	Description
✅ Efficient for sparse graphs	Fewer edges to check, especially in graphs with $V \gg E$
✅ Simple logic	Straightforward to understand and implement
✅ Handles disconnected graphs	Can find minimum spanning forest

❌ Disadvantages

Disadvantage	Explanation
❌ Requires edge sorting	Sorting edges adds $O(E \log E)$ overhead
❌ Needs Union-Find structure	More complex implementation than Prim's basic form
❌ Slower on dense graphs	More edges = more sorting and comparisons

📘 Applications of Kruskal's Algorithm

- Network design (LAN, road, power grid)
- Image segmentation
- Clustering in machine learning
- Finding connected components

📄 Kruskal's vs. Prim's Algorithm

Feature	Kruskal's Algorithm	Prim's Algorithm
Strategy	Edge-based	Vertex-based
Suitable for	Sparse graphs	Dense graphs
Data Structure	Disjoint Set (Union-Find)	Priority Queue (Min Heap)
Time Complexity	$O(E \log V)$	$O(E \log V)$
Cycle Detection	Union-Find	Visited array

Summary

- **Kruskal's Algorithm** builds MST by **selecting the smallest edges** while **avoiding cycles**.
 - It is **efficient for sparse graphs** and often easier to implement than Prim's for edge list representations.
 - Uses **Union-Find** to maintain disjoint sets for cycle checking.
-

Would you like:

- ☒ Python / C++ / Java code?
- ☒ A visual diagram for Kruskal's algorithm?
- ☒ Practice problems with solutions?

Let me know how you'd like to continue!

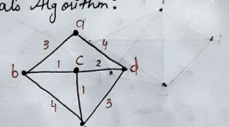
③ KRUSHKAL'S ALGORITHM:-

working

To exit full screen, press **Esc**

- (i) choose an edge of minimal weight.
- (ii) At each step, choose the edge whose inclusion will not create a circuit.
- (iii) If G has n vertices, stop after $(n-1)$ edges.

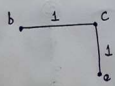
Que :- Find minimal spanning tree of a given graph by Kruskal's Algorithm.



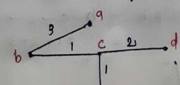
Sol :- In a graph G has 5 vertices \therefore the spanning tree has 4 edges.

Edges :- $bc, ce, cd, ab, de, be, ad$
 weight :- $1, 1, 2, 3, 3, 4, 4$

Now choose an edge have minimum weight; bc, ce



Now we choose the subsequent edges cd and ab we have



Then, the sum of weight = $1 + 1 + 2 + 3 = 7$.

✓ Definition

Dijkstra's Algorithm is a **greedy algorithm** that finds the **shortest path** from a single source vertex to all other vertices in a **weighted graph** (with **non-negative edge weights**).

💡 Key Idea

- Continuously select the **closest unvisited node** and update the shortest distances to its neighbors.
- Repeat until all vertices are visited.

Assumptions

- Works on **directed or undirected graphs**
 - All **edge weights must be ≥ 0** (non-negative)
 - Input: Graph $G(V, E)$, source vertex S
-

Data Structures Used

Structure	Purpose
Distance Array	Store shortest known distances
Priority Queue	Get the next closest node efficiently
Visited Set	Keep track of already processed nodes

Algorithm Steps

Step 1: Initialize

- $\text{dist}[\text{source}] = 0$
- $\text{dist}[\text{others}] = \infty$
- Use a **min-priority queue** to pick the next vertex with the **minimum distance**.

Step 2: Loop until the queue is empty

- Extract the node u with the smallest $\text{dist}[u]$
- For each neighbor v of u :
 - If $\text{dist}[v] > \text{dist}[u] + \text{weight}(u, v)$:
 - Update $\text{dist}[v]$
 - Push $(\text{dist}[v], v)$ into the priority queue

Step 3: Repeat until all nodes have been visited.

Python Pseudocode

python

Copy code

```
import heapq
```

```
def dijkstra(graph, source):
    n = len(graph)
    dist = [float('inf')] * n
    dist[source] = 0
    pq = [(0, source)] # (distance, node)

    while pq:
        d, u = heapq.heappop(pq)
        if d > dist[u]: # Already found better path
            continue
        for v, w in graph[u]:
            if dist[v] > dist[u] + w:
                dist[v] = dist[u] + w
                heapq.heappush(pq, (dist[v], v))
    return dist
```

Example

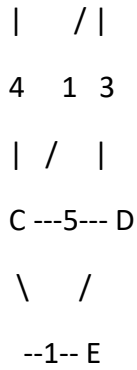
Graph

Let's say we have the following graph with 5 nodes (A–E = 0–4):

mathematica

Copy code

A ---2--- B



Edges (with weights):
A–B (2), A–C (4), B–C (1), B–D (3), C–D (5), C–E (1), D–E (2)

Step-by-step from source A (0):

Iteration	Node	Distance Updates	Final dist[]
Init	—	A=0, others=∞	[0, ∞, ∞, ∞, ∞]
1	A	B=2, C=4	[0, 2, 4, ∞, ∞]
2	B	C=3, D=5	[0, 2, 3, 5, ∞]
3	C	E=4	[0, 2, 3, 5, 4]
4	E	D=4	[0, 2, 3, 4, 4]
5	D	—	Final distances

✅ Final shortest distances from A:

mathematica

Copy code

A → A = 0

A → B = 2

A → C = 3

A → D = 4

A → E = 4

Time Complexity

Implementation Type	Time Complexity
---------------------	-----------------

Simple array (no heap)	$O(V^2)$
------------------------	----------

Binary heap + adjacency list	$O((V + E) \log V)$
------------------------------	---------------------

Fibonacci heap (advanced)	$O(E + V \log V)$
---------------------------	-------------------

Advantages

- Efficient for **sparse graphs** with **non-negative weights**
 - Always finds the **shortest path**
 - Simple and intuitive
-

Disadvantages

- **Does not work with negative edge weights**
 - Slightly **slower than A*** in some heuristic problems
 - Not suitable for **dynamic graphs** unless recomputed
-

Applications

- GPS / Navigation systems
 - Network routing (e.g., OSPF, RIP)
 - Game AI pathfinding
 - Robot motion planning
 - Real-time traffic apps
-

Summary

Feature Description

Input Graph + source vertex

Output Shortest path from source to all others

Type Greedy algorithm

Limitation Cannot handle negative weights

Efficiency $O((V + E) \log V)$ with a min-heap

Weighted Graph and Shortest Path :-
 A weighted graph is a graph in which each edge is associated with a non-negative integer $W(e)$ associated to each edge, this $W(e)$ is a weight of corresponding edge.

Ques:- Find the shortest path b/w a and f for the following graph :-

Sol:- Shortest Path in Weighted Graph :-
* Dijkstra's Algorithm :-

	a	b	c	d	e	f
0	∞	∞	∞	∞	∞	∞
0	3	4	∞	∞	∞	∞
0	1	3	6	∞	∞	∞
0	1	3	8	4	∞	∞
0	1	3	7	4	10	∞
0	1	3	7	4	9	9

Hence, the path is;
 $\{a, b, c, e, d, f\}$
 \times

Calculation for the shortest path a → b → c → e → d → f:
 $= 0 + 1 + 2 + 1 + 3 + 2 = 9$