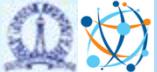




# DS221: Introduction to Scalable Systems

Topic: Algorithms and Data  
Structures



# L6: Algorithm Types

Algorithms



# Algorithm classification

- Algorithms that use a *similar problem-solving approach* can be grouped together
  - ▶ A classification scheme for algorithms
- Classification is neither exhaustive nor disjoint
- The purpose is not to be able to classify an algorithm as one type or another, but to *highlight the various ways in which a problem can be attacked*



# A short list of categories

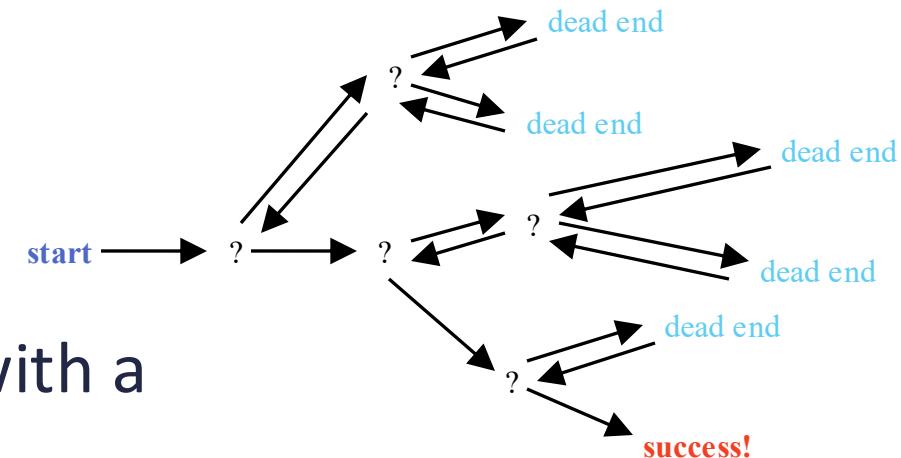
- Algorithm types we will consider include:
  1. Simple recursive algorithms
  2. Backtracking algorithms
  3. Divide and conquer algorithms
  4. Dynamic programming algorithms
  5. Greedy algorithms
  6. Branch and bound algorithms
  7. Brute force algorithms
  8. Randomized algorithms



# Simple Recursive Algorithms

- A simple **recursive algorithm**:
  1. Solves the base cases directly
  2. Breaks the problem into a smaller subproblem and recurses.
  3. Does some extra work to convert the solutions to the simpler subproblems into a solution to the given problem
- *Any seen so far?*
  - Tree traversal
  - Binary search over sorted array

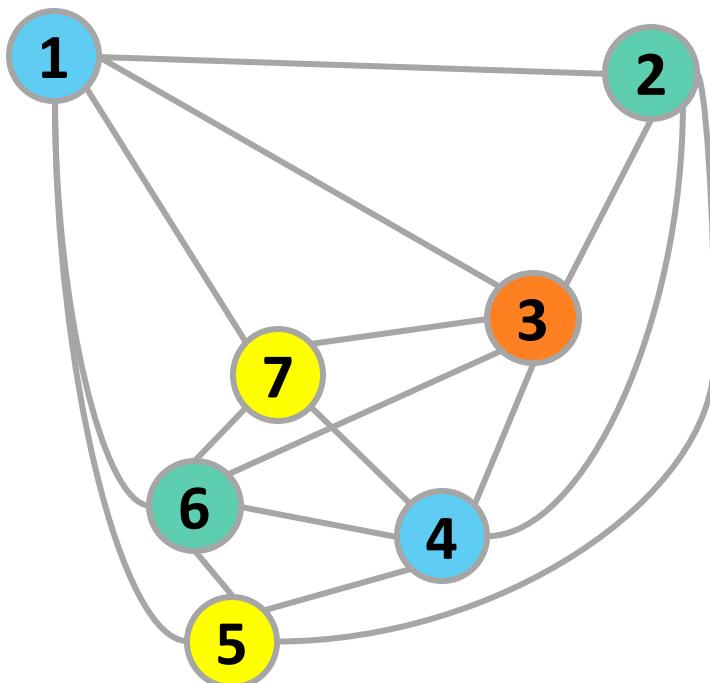
# Backtracking algorithms



- Explore the solution space with a depth-first recursive search
- At each step:
  - Check if a complete solution is reached → return it
  - Otherwise, for every available choice:
    - Make the choice
    - Recurse
    - If recursion yields a solution → return it
- If all choices fail → return failure

# Example

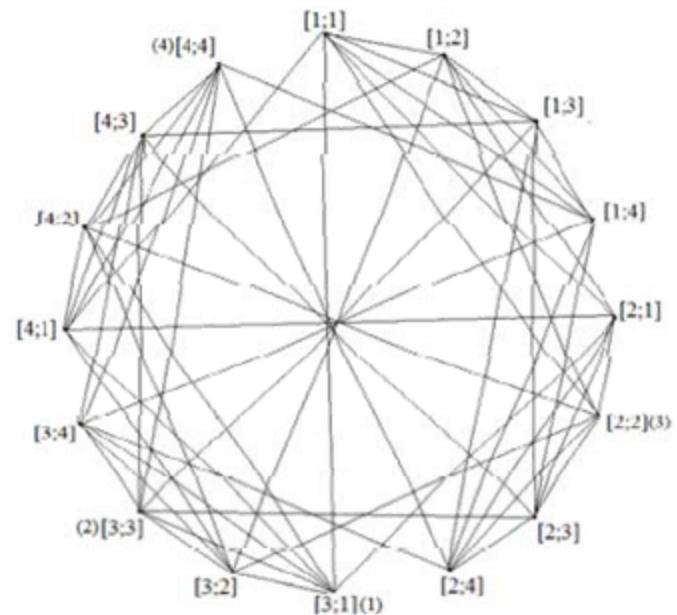
**Graph coloring:** Color the vertices of a graph such that no two adjacent vertices have the same color



4x4 Sudoku

[1;1]	[1;2]	[1;3]	[1;4]
[2;1]	[2;2]	[2;3]	[2;4]
1		2	
[4;1]	[4;2]	[4;3]	[4;4]

4



The above mentioned graph has 16 vertices and 56 edges.

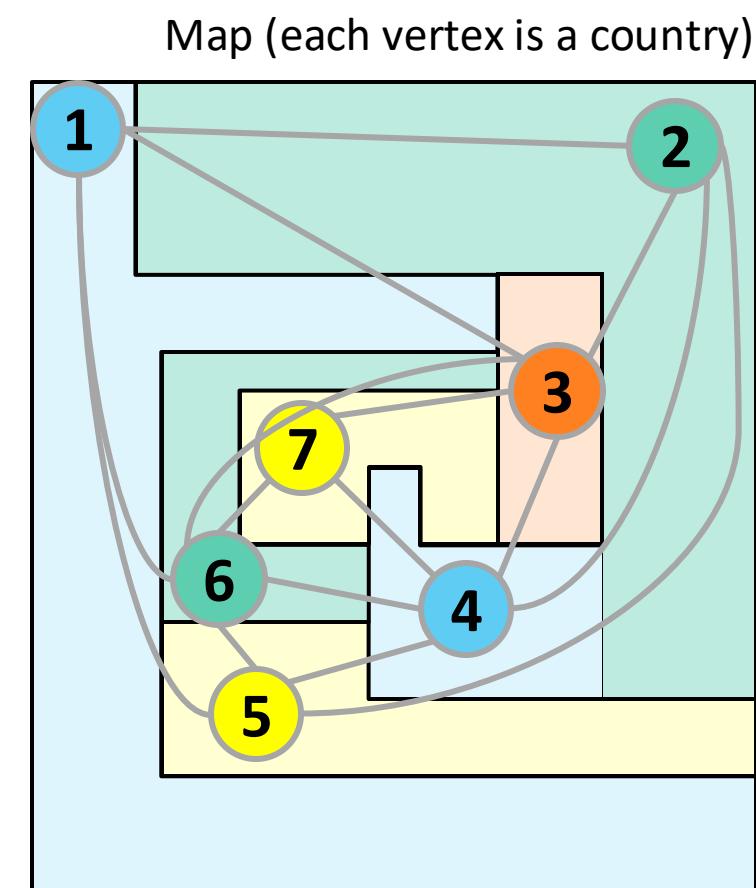


# Graph Coloring

- m-color problem
  - Given a graph, find out if its vertices can be colored with no more than  $m$  colors
  - $O(m^v)$
  
- The **Four-Color Theorem** states that any map on a plane can be colored with no more than four colors, so that no two neighbouring countries with a common border have the same color

# Sample backtracking algorithm

```
boolean explore(int ctry) {  
    if (ctry > map.size) return true  
  
    for (c = RED; c <= BLUE; c++)  
    {  
        if (okToColor(ctry, c)) {  
            map[ctry] = c;  
            if (explore(ctry + 1))  
                return true;  
            map[ctry] = NONE  
        }  
    }  
    return false  
}
```





# Divide and Conquer

- A **divide and conquer algorithm** consists of two parts:
  - ▶ *Divide* the problem into smaller subproblems of the same type, and solve these subproblems recursively
  - ▶ *Combine* the solutions to the subproblems into a solution to the original problem
- *Traditionally, an algorithm is only called “divide and conquer” if it contains at least two recursive calls*



# Binary search tree lookup?

- Compare the key to the value in the root
  - If the two values are equal, report success
  - If the key is less, search the left subtree
  - If the key is greater, search the right subtree

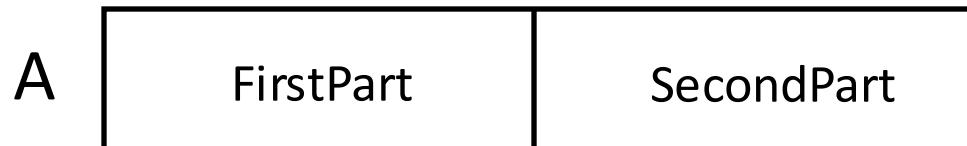
This is ***not*** a divide and conquer algorithm because even though the code contains two recursive calls, **only one branch** is actually explored at each recursion level.

- *E.g. Recursive binary search over an unsorted array.  
Search all elements.*
- *E.g. Merge Sort, Quick Sort*



# Merge Sort: Idea

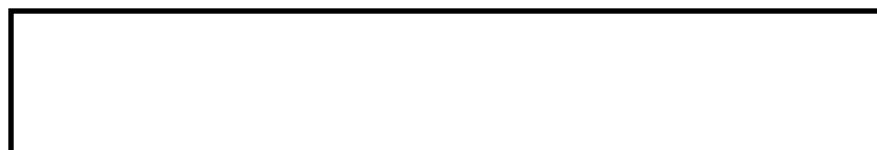
Divide into  
two halves



Recursively sort



Merge



A is sorted!

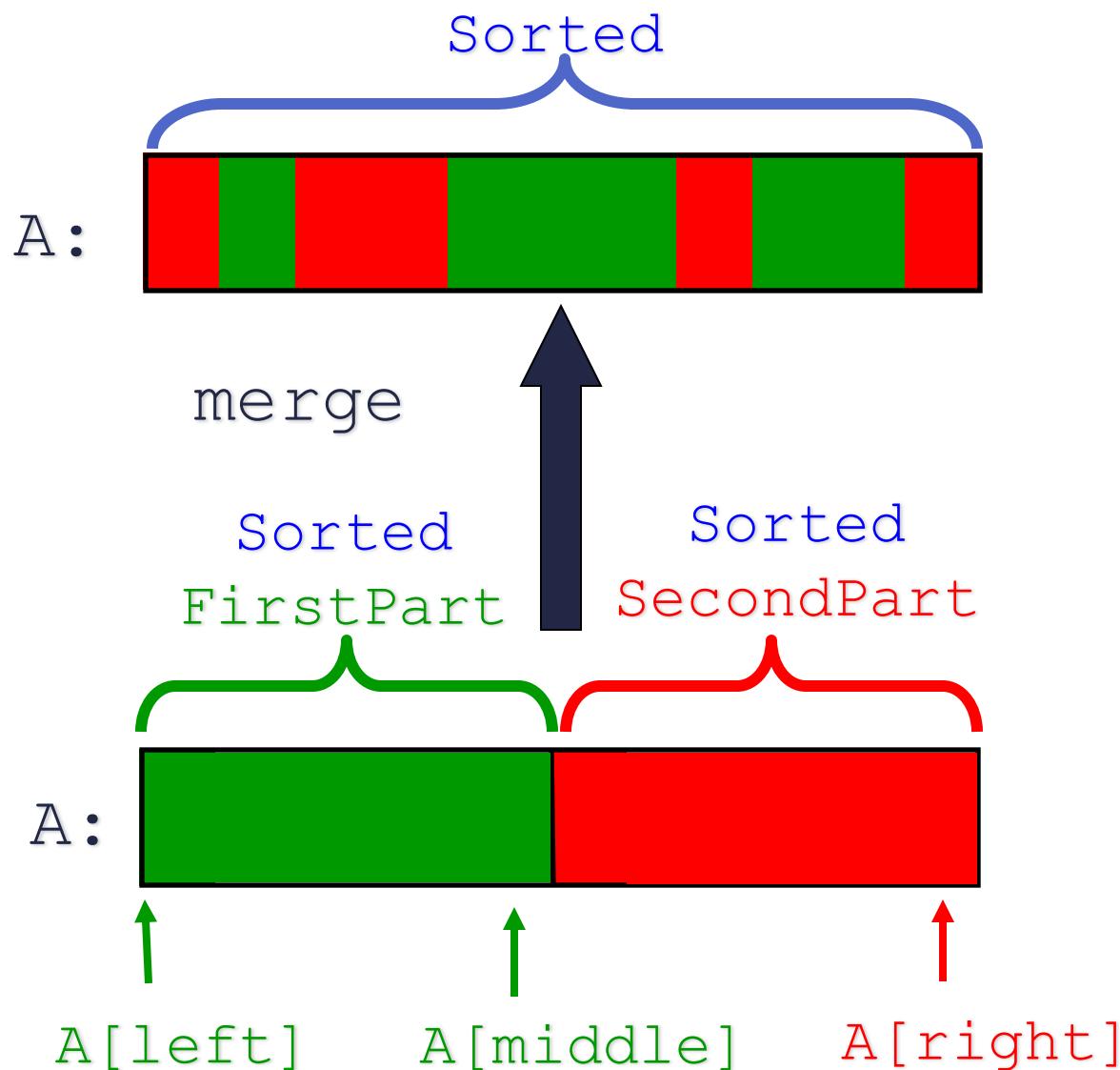


# Merge Sort: Algorithm

```
MergeSort (A, left, right)
    if (left >= right) return
    else {
        middle = Floor((left+right)/2)
        MergeSort(A, left, middle)           Recursive Call
        MergeSort(A, middle+1, right)
        Merge(A, left, middle, right)
    }
}
```

**Merge:** Given two sorted arrays,  
merges them into a single sorted array

# Merge-Sort: Merge





# Merge-Sort: Merge

A:



L:



R:

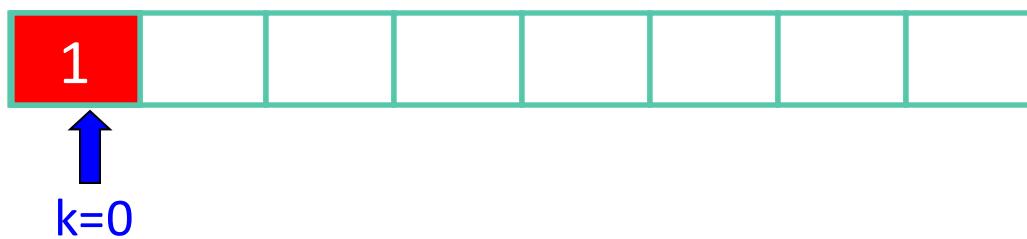


Temporary Arrays



# Merge-Sort: Merge

A:



L:



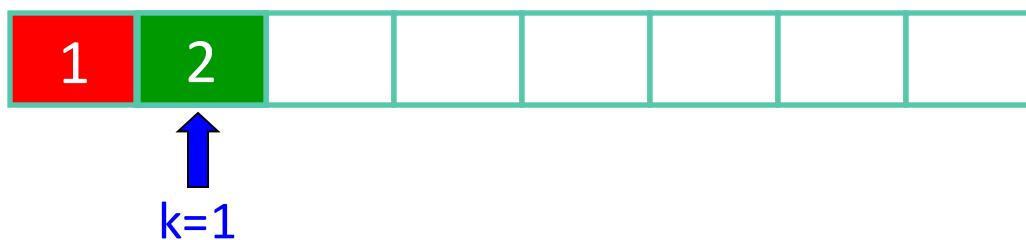
R:





# Merge-Sort: Merge

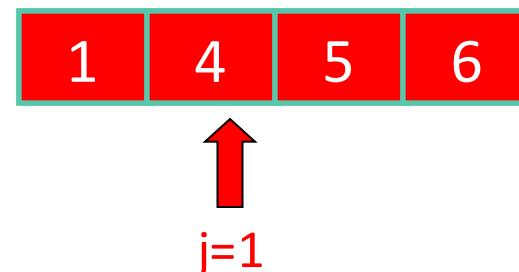
A:



L:



R:



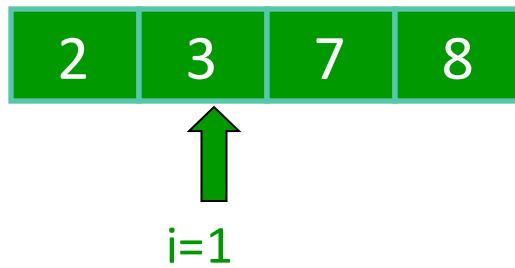


# Merge-Sort: Merge

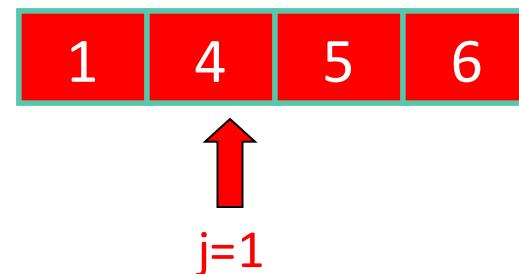
A:



L:



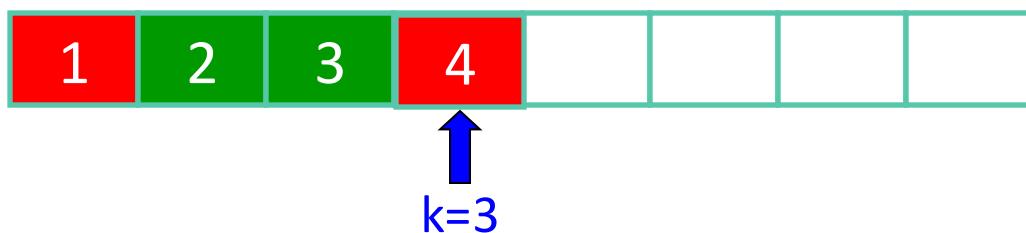
R:



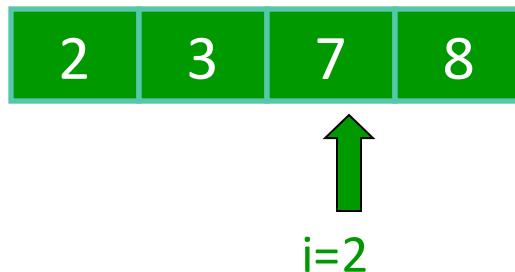


# Merge-Sort: Merge

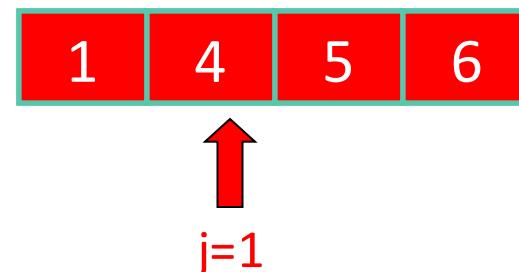
A:



L:



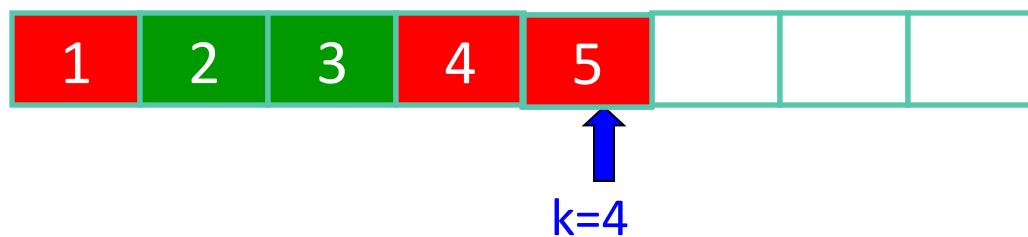
R:



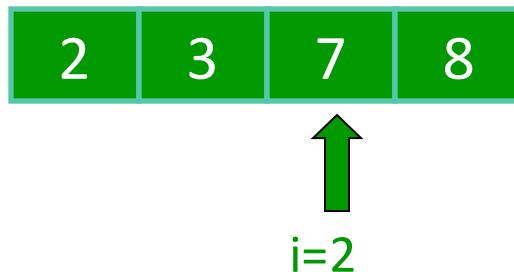


# Merge-Sort: Merge

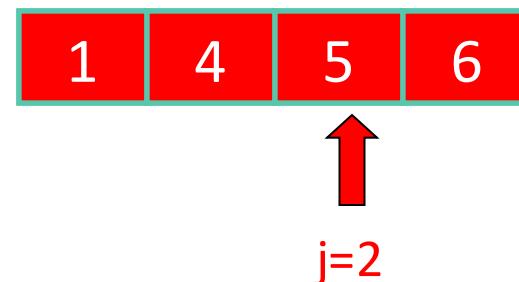
A:



L:



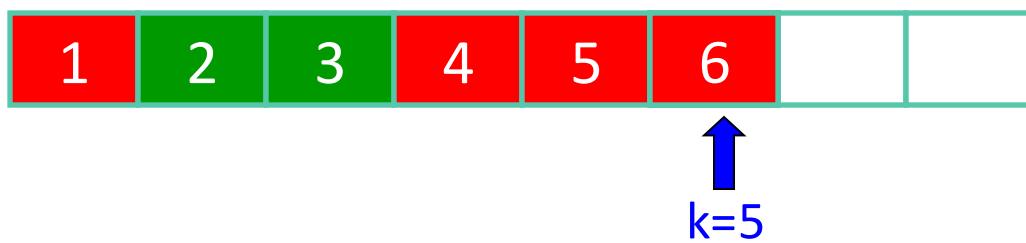
R:



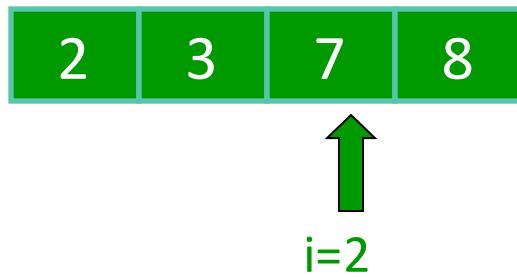


# Merge-Sort: Merge

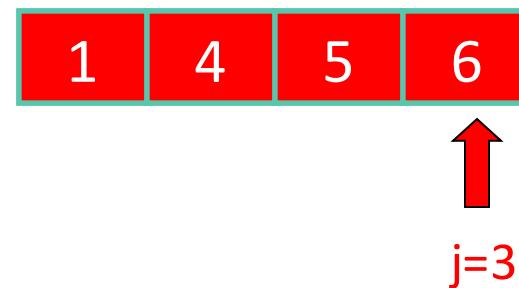
A:



L:



R:





# Merge-Sort: Merge

A:



↑  
k=6

L:



↑  
i=2

R:



↑  
j=4



# Merge-Sort: Merge

A:



↑  
k=7

L:



↑

i=3

R:



↑

j=4



# Merge-Sort: Merge

A:



↑  
k=8

L:



↑  
i=4

R:

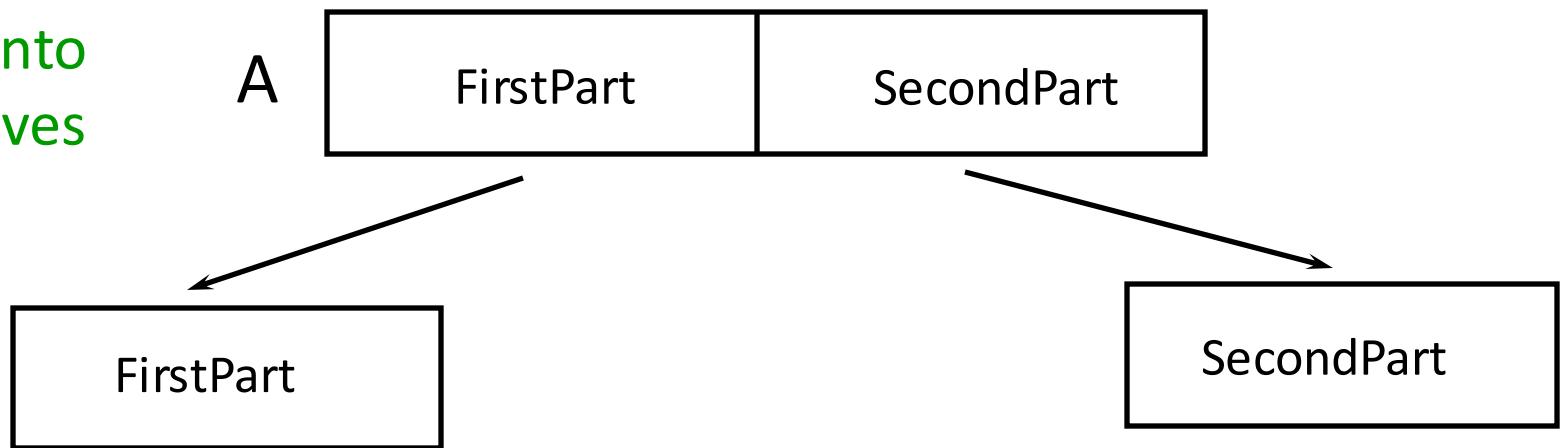


↑  
j=4



# Merge Sort

Divide into  
two halves



Why split into two, why not  $k$  ( $k > 2$ ) ?





# Live demo

- Comparison of merge sort implementations  
( $k=2,10,100$ )

[https://github.com/cjain7/DS221-Chirag-LiveDemos/tree/main/Lecture\\_10](https://github.com/cjain7/DS221-Chirag-LiveDemos/tree/main/Lecture_10)

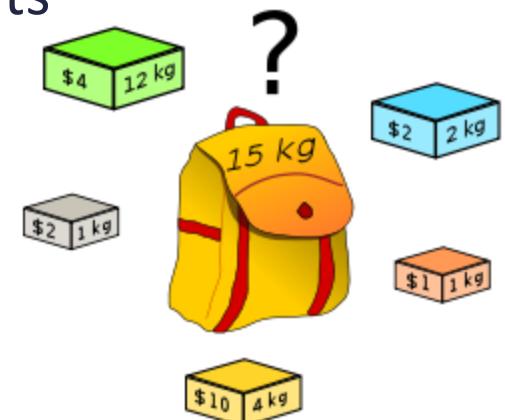


# Greedy algorithms

- An **optimization problem** is one in which you want to find, not just *a* solution, but the *best* solution
- A “greedy algorithm” sometimes works well for optimization problems
- A **greedy algorithm** works in phases: At each phase:
  - You take the best you can get right now, without regard for future consequences
  - You hope that by choosing a *local* optimum at each step, you will end up at a *global* optimum
- *Any seen so far?*
- Djikstra’s Shortest path problem
  - Greedily pick the shortest among the unprocessed vertices

# Knapsack Problem

- We are given a set of  $n$  items, where each item  $i$  is specified by a size  $s_i$  and a value  $v_i$ . We are also given a size bound  $S$  (the size of our knapsack).
- The goal is to find the subset of items of maximum total value such that sum of their sizes is at most  $S$  (i.e., they all fit into the knapsack).
  - Exponential time to try all possible subsets





# Knapsack Problem

- 0-1 Knapsack:

- ▶  $n$  items
- ▶ Must **leave or take** (i.e. 0-1) each item (e.g. bars of gold of different sizes and values)

- Fractional Knapsack:

- ▶  $n$  items
- ▶ Can take **fractional part** of each item (e.g. gold dust)



# Greedy Solution 1

- From the remaining objects, select the object with maximum value that fits into the knapsack
- *Does not guarantee an optimal solution*
- E.g.,  $n=3$ ,  $s=[100,10,10]$ ,  $v=[20,15,15]$ ,  $S=105$



# Greedy Solution 2

- Select the one with the maximum value density  $v_i/s_i$  that fits into the knapsack
- *Still does not guarantee an optimal solution*
- E.g.,  $n=3$ ,  $s=[20,15,15]$ ,  $v=[40,25,25]$ ,  $S=30$
- However, this greedy approach is optimal for fractional knapsack!
  - ▶ Proof?



# Greedy Solution 2 [fractional knapsack]

## ■ Greedy algorithm:

- Sort items by their density ( $v_i/s_i$ ) in non-increasing order
- Take as much possible from the highest-density item, then move to the next, until the size bound (capacity)  $S$  is reached

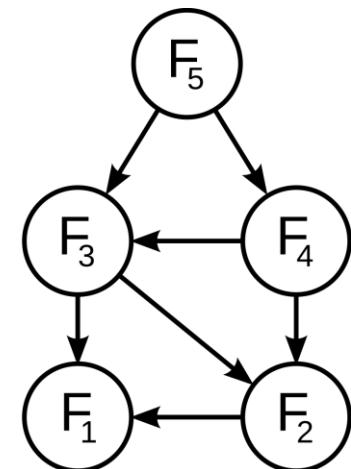
## ■ Proof of optimality:

- Without loss of generality, assume that the  $n$  items are indexed by their density, i.e.,  $v_1/s_1 \geq v_2/s_2 \geq \dots \geq v_n/s_n$
- Let  $g_1, g_2, \dots, g_n$  be the fraction of items picked by greedy
- Let  $f_1, f_2, \dots, f_n$  be the fraction of items picked by another optimal solution  $X$  that is not greedy
- Let  $i$  be the smallest index such that  $f_i \neq g_i$
- Observe that  $f_i$  must be less than  $g_i$ . And there must exist some  $k$  such that  $k > i$  and  $f_k > g_k$
- If we transfer a small amount of capacity  $\delta$  from item  $k$  to item  $i$  in solution  $X$ , then the value improves by  $\delta \times (v_i/s_i - v_k/s_k)$ , which is  $\geq 0$
- Repeating this exchange process transforms any optimal solution into the greedy solution. The greedy solution is optimal for fractional knapsack.

# Dynamic Programming (DP)

- Dynamic programming is generally used for optimization problems
  - Multiple solutions exist, need to find the best one
  - The problem should have two properties
    - **Optimal substructure:** Optimal solution can be constructed from optimal solutions to subproblems
    - **Overlapping subproblems:** Any recursive algorithm solving the problem should solve the same sub-problems over and over
- *This differs from Divide and Conquer, where subproblems generally need not overlap*

Fibonacci sequence:  $F_i = F_{i-1} + F_{i-2}$



The subproblem graph for the Fibonacci sequence. The fact that it is not a tree indicates overlapping subproblems.



# Fibonacci numbers

- $n_i = n_{(i-1)} + n_{(i-2)}$
- 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, ...
- To find the  $n^{\text{th}}$  Fibonacci number:
  - If  $n = 0$ , return 1. If  $n = 1$ , return 1
  - Otherwise, compute `fibonacci(n-1)` and `fibonacci(n-2)`
  - Return the sum of these two numbers
- This is a *recursive* algorithm but it is computationally expensive
- Time complexity is exponential  $O(2^n)$ 
  - Binary tree of height ‘n’ with  $f(n)$  having two children,  $f(n-1)$ ,  $f(n-2)$



# Fibonacci numbers again

- To find the  $n^{\text{th}}$  Fibonacci number:
  - If  $n=0$ , return 0. If  $n=1$ , return 1.
  - If  $n>1$ , then **compute or retrieve following from a table**:
    - $\text{fibonacci}(n-1)$
    - $\text{fibonacci}(n-2)$
  - Add these two values
  - **Store the result in a table** and return it
- In this algorithm, the table of previously computed values is being reused in future computations.
- Other examples: *Floyd–Warshall All-Pairs Shortest Path (APSP) algorithm, Towers of Hanoi, ...*



# Back to the 0-1 Knapsack Problem

- We are given a set of  $n$  items, where each item  $i$  is specified by a size  $s_i$  and a value  $v_i$ . We are also given a size bound  $S$  (the size of our knapsack).
- 0-1 Knapsack:
  - $n$  items
  - Must **leave or take** each item



# DP for 0-1 Knapsack

## Define subproblems:

Let  $\text{arr}[i][Z]$  represent the **maximum value achievable** using the first  $i$  items and knapsack size limit  $Z$

## Recurrence:

$$\text{arr}[i][Z] = \begin{cases} \text{arr}[i - 1][Z] & \text{if } s_i > Z \\ \max( \text{arr}[i - 1][Z], v_i + \text{arr}[i - 1][Z - s_i] ) & \text{otherwise} \end{cases}$$

## Base case:

$\text{arr}[i][0] = 0$  for all  $i$

$\text{Arr}[0][Z] = 0$  for all  $Z$

## Final solution

$\text{arr}[n][S]$



# Pseudocode

Create two-dimensional array arr[0..n][0..S]

Time and space complexity?

```
# Base case
for Z = 0 to S
    arr[0][Z] = 0
for i = 0 to n
    arr[i][0] = 0
```

```
# Fill DP table
for i = 1 to n
    for Z = 1 to S
        if sizes[i] > Z
            arr[i][Z] = arr[i-1][Z]
        else
            arr[i][Z] = max( arr[i-1][Z], values[i] + arr[i-1][Z - sizes[i]] )
return arr[n][S]
```



# LCS problem (Try on your own)

- We are given two strings X and Y, find the **length** of their **longest common substring**.
- Example:
  - X = "abcdef"
  - Y = "zbcdcfg"
  - Then, length of longest common substring = 4 ("bcdf")
- Hint:
  - Define subproblem: Compute length of the longest common substring **ending at** position i in X and position j in Y
  - Recursion? Base case? Final solution?



# Brute force algorithm

- A **brute force algorithm** simply tries *all* possibilities until a satisfactory solution is found
- Such an algorithm can be:
  - **Optimizing:** Find the *best* solution. This may require finding all solutions, or if a value for the best solution is known, it may stop when any best solution is found
    - Example: Finding the best path for a traveling salesman
  - **Satisficing:** Stop as soon as a solution is found that is *good enough*
    - Example: Finding a traveling salesman path that is within 10% of optimal



# Improving brute force algorithms

- Often, brute force algorithms require exponential time
- Various *heuristics* and *optimizations* can be used
  - Heuristic: A “rule of thumb” that helps you decide which possibilities to look at first
  - Optimization: In this case, a way to eliminate certain possibilities without fully exploring them



# Randomized algorithms

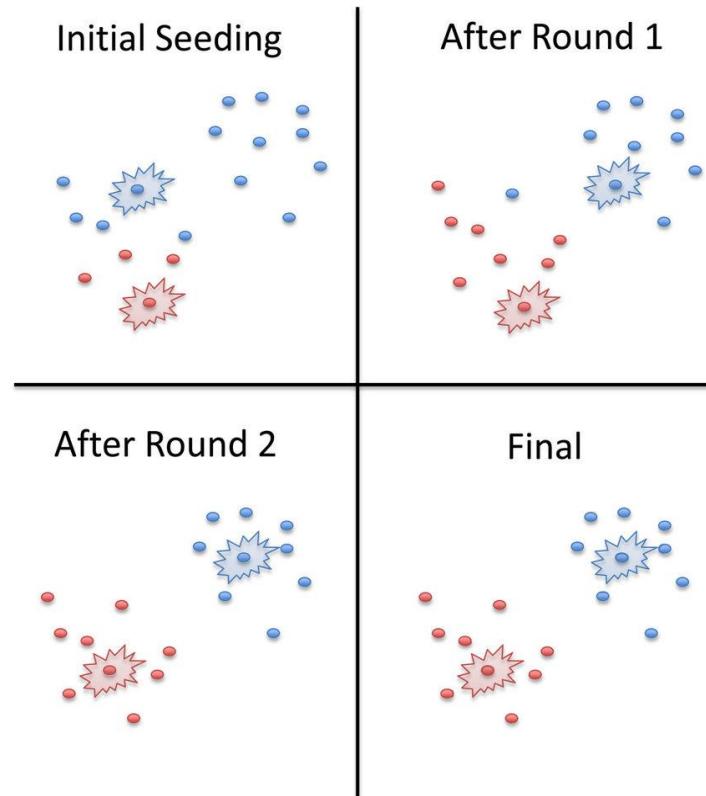
- A **randomized algorithm** uses a random number at least once during the computation to make a decision
  - Example: In Quicksort, using a random number to choose a pivot
  - Example: Trying to factor a large number by choosing random numbers as possible divisors



# k-means clustering

## ■ Steps

1. **Initialize:** Choose  $k$  initial centroids **randomly**.
2. **Assignment step:** Assign each data point to the cluster with the nearest centroid (using a distance measure, e.g., Euclidean).
3. **Update step:** Recompute each centroid as the mean of all points currently assigned to that cluster.
4. **Repeat** steps 2–3 until:
  - Cluster assignments no longer change, or
  - A maximum number of iterations is reached.





# Reading

- Online resources on algorithms
- <https://www.cs.cmu.edu/~avrim/451f09/lectures/lecture1001.pdf>