

Algorithms & Data Structures II

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Dynamic Programming

Weighted Interval Scheduling

The idea: Sort by finish time and select

$\text{OPT}(j) = \max(v[j]) + \text{OPT}(p[j]), \text{OPT}(j-1))$. Either you take job j , and skip conflicts, or don't take it. The algorithm runs in $O(n \log n)$ time, where n is the number of jobs.

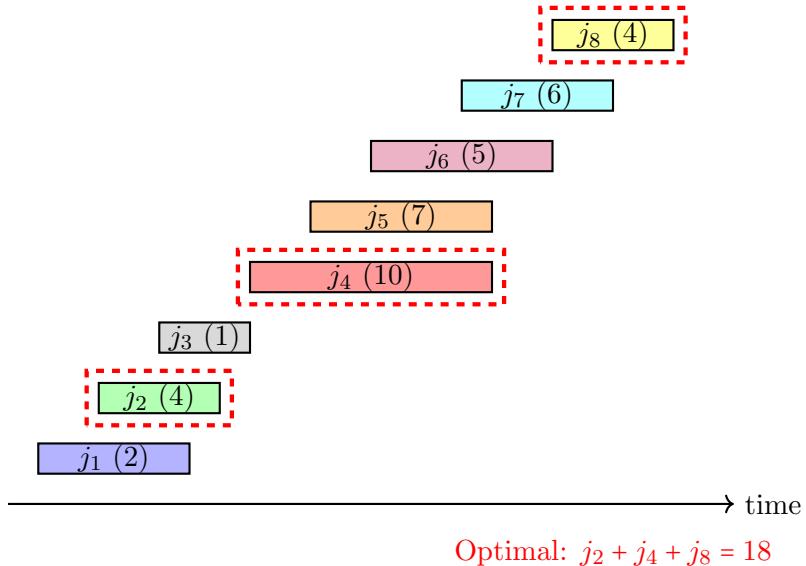


Figure 1: Weighted Interval Scheduling Example: Jobs are sorted by finish time. The optimal solution selects non-overlapping jobs with maximum total value.

Knapsack

The problem: Fill a backpack with as many books as possible.

$\text{OPT}(i, w) = \max(\text{OPT}(i-1, w), v[i] + \text{OPT}(i-1, w-w[i]))$ The option is to take an item i or not and the algorithm runs in $O(nW)$ time, where n is the number of items and W is knapsack capacity. The algorithm creates a 2D table consisting of $n \times W$

Sequence Alignment

The problem: Match characters, gap in X , or gap in Y . The running time of this algorithm is

Max Flow & Min Cut

Flow Algorithms

Name	Running Time	Explanation	Notes
Ford-Fulkerson	$O(f \cdot m)$	$ f = \text{max flow value}$ $m = \# \text{ edges}$	Pseudopolynomial; can fail to terminate
Scaling	$O(m^2 \log C)$	$C = \text{max edge capacity}$	Weakly polynomial; assumes integer capacities
Edmonds-Karp	$O(m^2 n)$	$n = \# \text{ vertices}$ $m = \# \text{ edges}$	Uses BFS; strongly polynomial

Running the algorithms

When running the algorithms by hand, just use a basic approach—it's manageable when the graph is reasonably simple. For min-cut, find the saturated edges (at capacity) along the residual graph boundary between reachable and unreachable vertices from the source.

Flow Problem Recipe

Build the Graph

- Vertices (source + sink)
- Edges (capacities + direction)

Describe the Algorithm

- Find max flow (m) and INSERT ALGORITHM
- Return an answer

Analyse Runtime

- Build Parameters from question
- Remember the time it takes to build the graph

Randomised Algorithms

Expected Value

Expected value is the average outcome over many trials. For a discrete random variable X :

$$\mathbb{E}[X] = \sum_i x_i \cdot \mathbb{P}[X = x_i]$$

Common trick: Use indicator random variables. If $X = X_1 + X_2 + \dots + X_n$ where each X_i is an indicator (0 or 1), then:

$$\mathbb{E}[X] = \sum_{i=1}^n \mathbb{E}[X_i] = \sum_{i=1}^n \mathbb{P}[X_i = 1]$$

Geometric distribution: If success probability is p , then expected number of trials until first success is $\frac{1}{p}$.

Example - QuickSort: Let X_{ij} be an indicator that equals 1 if elements i and j are compared, 0 otherwise. Total comparisons:

$$X = \sum_{i < j} X_{ij} \implies \mathbb{E}[X] = \sum_{i < j} \mathbb{E}[X_{ij}] = \sum_{i < j} \mathbb{P}[i \text{ and } j \text{ compared}]$$

Elements i and j are compared if one is chosen as pivot before any element between them, so $\mathbb{P}[i \text{ and } j \text{ compared}] = \frac{2}{j-i+1}$. Summing gives $\mathbb{E}[X] = O(n \log n)$.

Useful Sums

$$\sum_{n=0}^{\infty} x^n = \frac{1}{1-x}, \quad |x| < 1$$

$$\sum_{n=0}^{\infty} n \cdot x^n = \frac{x}{(1-x)^2}, \quad |x| < 1$$

$$\sum_{k=1}^n \frac{1}{k} = H(n), \quad \ln(n) < H(n) < \ln(n) + 1$$

$$\mathbb{P}[\text{first success in round } j] = (1-p)^{j-1} p$$

$$\mathbb{E}[X] = \sum x_i \cdot \mathbb{P}[X = x_i] \quad \text{where } x_i \in \text{possible outcomes}$$

$$\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

$$\text{if } \mathbb{P}[\text{success}] = p \text{ then } \mathbb{E}[\#\text{ tries to success}] = \frac{1}{p}$$

Hashing

Chained Hashing

Store elements in array of linked lists. Each element x goes to list at $A[h(x)]$. Operations take $O(|A[h(x)]| + 1)$ time. With universal hashing, expected $O(1)$ time per operation.

Linear Probing

Store elements directly in array. If $A[h(x)]$ is occupied, place x in next empty slot (wrapping around). Forms clusters of consecutive elements. Operations take $O(C(h(x)) + 1)$ time where $C(i)$ is cluster size. Cache-efficient but DELETE is $O(n^2)$.

Hash Functions

Universal hashing: Family H is universal if for any $x \neq y$, $\Pr[h(x) = h(y)] \leq \frac{1}{m}$ for random $h \in H$.

Dot product hashing: For $x = (x_1, x_2, \dots, x_r)$ in base m (prime), define

$$h_a(x) = (a_1 x_1 + a_2 x_2 + \dots + a_r x_r) \bmod m$$

where $a = (a_1, \dots, a_r)$ chosen randomly. This family is universal.

Performance Comparison

Data Structure	SEARCH	INSERT	DELETE	Space
Linked List	$O(n)$	$O(n)$	$O(n)$	$O(n)$
BBST	$O(\log n)$	$O(\log n)$	$O(\log n)$	$O(n)$
Direct Addressing	$O(1)$	$O(1)$	$O(1)$	$O(U)$
Chained Hashing (universal)	$O(1)$	$O(1)$	$O(1)$	$O(n)$
Linear Probing	$O(C(h(x)) + 1)$	$O(C(h(x)) + 1)$	$O(n^2)$	$O(n)$

· Expected time (when using universal hash function)

Amortised Analysis

Aggregate Method

The idea: Analyze the total cost $T(m)$ of a worst-case sequence of m operations, then compute the amortized cost as $T(m)/m$ per operation.

Accounting Method

Assign a *cost* \hat{c}_i to each operation. When $\hat{c}_i > c_i$, store the difference as credits. When $\hat{c}_i < c_i$, use stored credits to pay. Ensure $\sum_{i=1}^m \hat{c}_i \geq \sum_{i=1}^m c_i$ always holds.

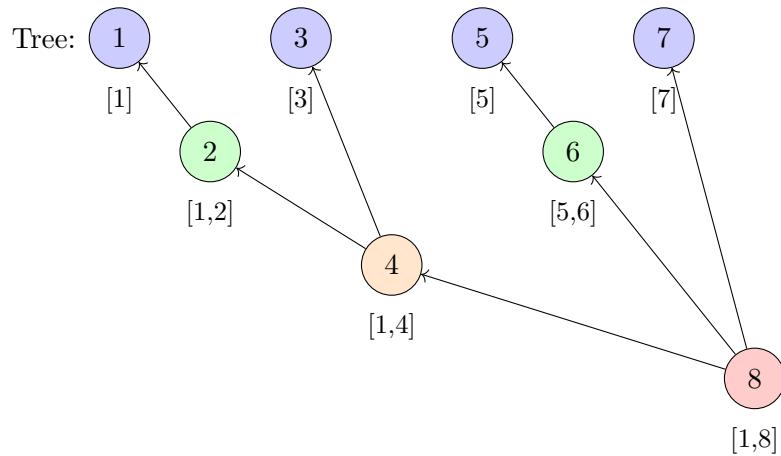
Potential Method

Define a potential function $\Phi(D)$ that maps the data structure state to a real value. Set amortized cost $\hat{c}_i = c_i + \Phi(D_i) - \Phi(D_{i-1})$. Require $\Phi(D_i) \geq 0$ for all i and $\Phi(D_0) = 0$.

Partial Sums & Dynamic Arrays

Partial Sums (Fenwick Trees)

A fenwick tree is effectively binary tree consisting of only the right child. This allows for an in-place data structure to compute the partial sum.



Example

here is an example on how to calculate a fenwick tree.

Index:	1	2	3	4	5	6	7	8
Value:	3	2	5	1	4	6	2	3

Index:	1	2	3	4	5	6	7	8
BIT:	3	2	5	1	4	6	2	3

Index:	1	2	3	4	5	6	7	8
BIT:	3	2	5	1	4	6	2	3

Index:	1	2	3	4	5	6	7	8
BIT:	3	5	5	1	4	6	2	3

Index:	1	2	3	4	5	6	7	8
BIT:	3	5	5	1	4	6	2	3

Index:	1	2	3	4	5	6	7	8
BIT:	3	5	5	11	4	6	2	3

Index:	1	2	3	4	5	6	7	8
BIT:	3	5	5	11	4	6	2	3

Index:	1	2	3	4	5	6	7	8
BIT:	3	5	5	11	4	10	2	3

Index:	1	2	3	4	5	6	7	8
BIT:	3	5	5	11	4	10	2	3

Index:	1	2	3	4	5	6	7	8
BIT:	3	5	5	11	4	10	2	26

Final Fenwick Tree:

Index:	1	2	3	4	5	6	7	8
BIT:	3	5	5	11	4	10	2	26
Range:	[1]	[1,2]	[3]	[1,4]	[5]	[5,6]	[7]	[1,8]

Dynamic Arrays

Rotated Array

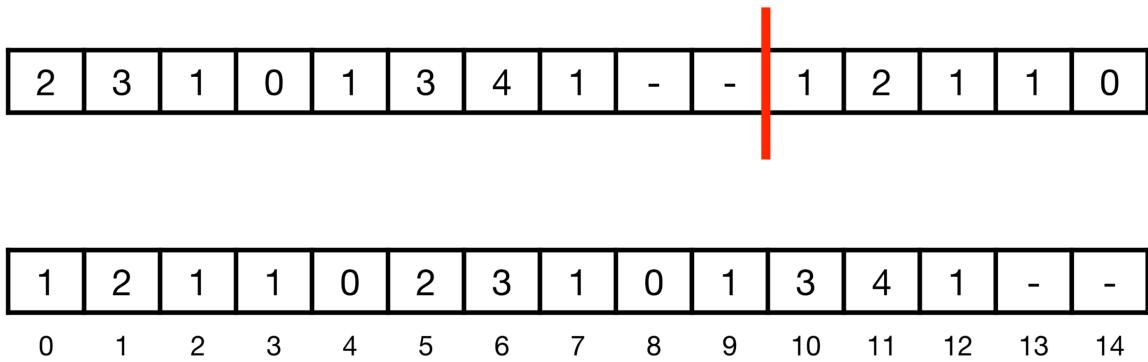


Figure 2: 1 level rotated array

Key idea: Store offset to mark the start of the array.

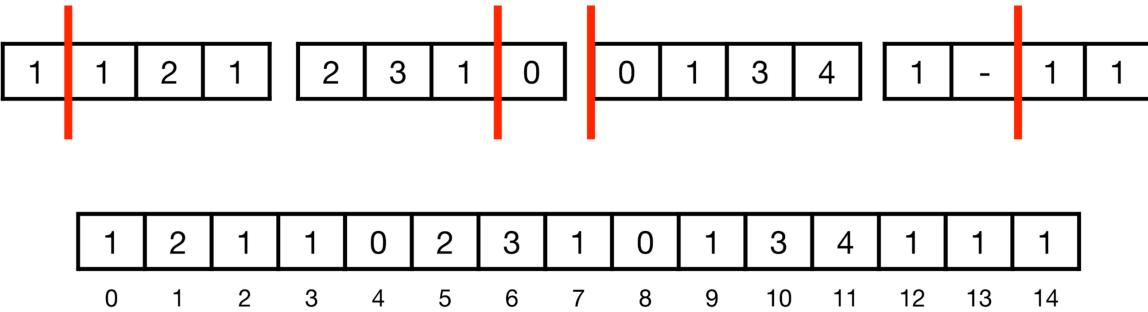


Figure 3: 2 level rotated array

Key idea: Split into \sqrt{n} rotated buckets of size \sqrt{n} . When inserting/deleting, rebuild one bucket in $O(\sqrt{n})$ time, then propagate overflow/underflow.

Data Structure	Access	Insert	Delete	space
1 level rotated array	$O(1)$	$O(\sqrt{n})$	$O(\sqrt{n})$	$O(n)$
2 level rotated array	$O(1)$	$O(n^\varepsilon)$	$O(n^\varepsilon)$	$O(n)$

In a k -level rotated array, $\varepsilon = \frac{1}{k}$ determines that you partition n elements into $\sqrt[k]{n}$ buckets of size $\sqrt[k]{n}$ each, giving $O(n^{1/k}) = O(n^\varepsilon)$ time for INSERT/DELETE operations.

NP Completeness

Boils down to if a problem is solvable in polynomial time or non-deterministic polynomial time. The mindset I have for this is best describes via exercise 2 from week *NP Completeness*.

Example - Customer Uniqueness (KT 8.2)

A store trying to analyse the behavior of its customers will often main a two-dimensional array A , where the rows correspond to its customers and the columns correspond to the products it sells. The entry $A[i, j]$ specifies the quantity of project j that has been purchased by customer i .

Here's a tiny example of such an array A

	liquid detergent	beer	diapers	cat litter
Raj	0	6	0	3
Alanis	2	0	0	7
Chelsea	0	0	0	7

One thing that a store might want to do with this data is the following. Let us say that a subset S off the customers is *diverse* if no two of the customers in S have ever bought the same product (i.e., for each product, at most one of the customers in s has ever bought it). A diverse set of customers can be useful, for example, as a target pool for market research.

We can now define the Diverse Subset Problem as follows: Given an $m \times n$ array A as defined above, and a number $k \leq m$, is there a subset of at least k of customers that is *diverse*?

Show that Diverse subset in NP-complete.

Solution

We show that $IS \leq_p DS$, where IS is Independent Set and DS is Diverse Subset.

Given a graph $G = (V, E)$ with $|V| = m$ vertices and $|E| = n$ edges, construct an $m \times n$ matrix A where vertices are customers (rows) and edges are products (columns). For each edge $(u, v) \in E$, set $A[u, (u, v)] = 1$ and $A[v, (u, v)] = 1$ (all other entries are 0).

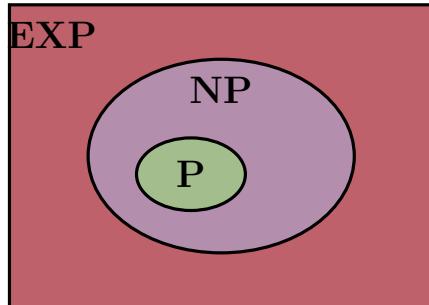
Now G has an independent set of size k if and only if A has a diverse subset of size k . Since the construction takes polynomial time, DS is NP-complete.

List of NP-complete Problems

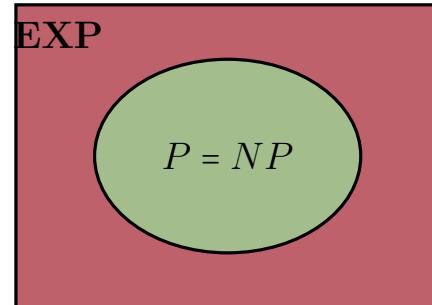
- Subset Sum
- Independent Set \otimes
- Vertex Cover \otimes
- Set Cover
- Longest Path \otimes
- Max Cut \otimes
- 3-Coloring \otimes

- Hamiltonian Cycle \otimes
- Travelling Salesperson \otimes

Is $P = NP$?



If $P \neq NP$



If $P = NP$