Dynamic Programming Algorithms

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Introduction

In our study of divide-and-conquer algorithms, we noticed that a problem seemed conducive to a divide-and-conquer approach provided

1. it could be divided into one or more subproblems of smaller size that could be recursively solved, and
2. solutions to the subproblems could be combined to form the solution to the original problem within a reasonable (i.e. bounded by a polynomial) number of steps.

Another key property that allows divide-and-conquer algorithms to succeed is that each subproblem occurs at most once in the computation tree induced by the recursion. For example, in quicksort once a portion of the original array has been sorted there is no need to sort it again.

However, the *top down* recursive approach is oftentimes not appropriate for some problems because a top down approach to solving them may cause some sub-problems to re-solved an exorbitant number of times in the computation tree. Consider the following example.

Example 1. The **Fibonacci sequence** $f_0, f_1, \ldots$ is recursively defined as follows:

- **base case.** $f_0 = 0$ and $f_1 = 1$
- **recursive case.** for $n \geq 2$, $f_n = f_{n-1} + f_{n-2}$.

Show that the following recursive algorithm for computing the n th Fibonacci number has exponential complexity with respect to n.

```
int fib(int n)
{
    if(n == 0)
        return 0;
    if(n==1)
        return 1;
    return fib(n-1) + fib(n-2);
}
```

Example 1 Continued.

The above recursive algorithm has a simple remedy that characterizes a *dynamic programming* algorithm. On input n, rather than make blind recursive calls, we instead store f_0 and f_1, and use these values to compute f_2. After storing f_2, we then compute f_3 using f_1 and f_2. This process continues until f_n has been computed. We call this approach a **bottom-up** approach, since the *focus* is on first computing the solutions to smaller subproblems, and then using those solutions to compute the solutions for larger subproblems, and eventually solving the original problem.

A **dynamic-programming algorithm** is similar to a divide-and-conquer algorithm in that it attempts to solve a problem instance by relating it to the solutions of sub-problem instances via a recurrence equation. For such an equation a subproblem-instance solution may need to be referenced several times. For this reason, each subproblem-instance solution is stored in a table for future reference.

The following are some problems that may be solved using a dynamic-programming algorithm.

0-1 Knapsack Given items $x_1, \ldots, x_n$, where item x_i has weight w_i and profit p_i (if it gets placed in the knapsack), determine the subset of items to place in the knapsack in order to maximize profit, assuming that the sack has weight capacity M.

Longest Common Subsequence Given an alphabet Σ, and two words X and Y whose letters belong to Σ, find the longest word Z which is a (non-contiguous) subsequence of both X and Y.

Optimal Binary Search Tree Given a set of keys $k_1, \ldots, k_n$ and weights $w_1, \ldots w_n$, where w_i is proportional to how often k_i is accessed, design a binary search tree so that the weighted cost of accessing a key is minimized.

Matrix Chain Multiplication Given a sequence of matrices that must be multiplied, parenthesize the product so that the total multiplication complexity is minimized.

All-Pairs Minimum Distance Given a directed graph $G = (V, E)$, find the distance between all pairs of vertices in V.

Polygon Triangulation Given a convex polygon $P =< v_0, v_1, \ldots, v_{n-1} >$ and a weight function defined on both the chords and sides of P, find a triangulation of P that minimizes the sum of the weights of which forms the triangulation.

Bitonic Traveling Salesperson given n cities $c_1, \ldots, c_n$, where c_i has grid coordinates (x_i, y_i), and a cost matrix C, where entry C_{ij} denotes the cost of traveling from city i to city j, determine a left-to-right followed by right-to-left Hamilton-cycle tour of all the cities which minimizes the total traveling cost. In other words, the tour starts at the leftmost city, proceeds from left to right visiting a subset of the cities (including the rightmost city), and then concludes from right to left visiting the remaining cities.

Viterbi's algorithm for context-dependent classification Given a set of observations $\vec{x}_1, \ldots, \vec{x}_n$ find the sequence of classes $\omega_1, \ldots, \omega_n$ that are most likely to have produced the observation sequence.

Edit Distance Given two words u and v over some alphabet, determine the least number of edits (letter deletions, additions, and changes) that are needed to transform u into v.

0-1 Knapsack

0-1 Knapsack: given items $x_1, \ldots, x_n$, where item x_i has weight w_i and profit p_i (if its placed in the knapsack), determine the subset of items to place in the knapsack in order to maximize profit, assuming that the sack has capacity M.

A recurrence for 0-1 Knapsack can be derived by making the following observations about an optimal solution.

Case 1 The optimal solution includes x_n. Then the rest of the solution is the optimal solution for the knapsack problem in which items $x_1, \ldots, x_{n-1}$ are given (same weights and profits as before), and for which the sack capacity is now $M - w_n$.

Case 2 The optimal solution does not include x_n. Then the solution is the optimal solution for the knapsack problem in which items $x_1, \ldots, x_{n-1}$ are given (same weights and profits as before), and for which the sack capacity is M.

We can generalize this observation by considering the sub-problem where items $x_1, \ldots, x_i$ are to be placed into a knapsack with capacity c. Letting $P(i, c)$ denote the maximum profit for this problem, then the above cases lead to the recurrence

$$P(i,c) = \begin{cases} 0 & \text{if } i = 0 \text{ or } c \leq 0 \\ \max(P(i-1,c), P(i-1,c-w_i) + p_i) & \text{if } w_i \leq c \\ P(i-1,c) & \text{otherwise} \end{cases}$$

Of course, we ultimately desire to compute $P(n, M)$ which may be found by be computing each entry of the matrix $P(i, c)$, for $0 \leq i \leq n$, and $0 \leq c \leq M$. Thus, the algorithm has a running time of $\Theta(nM)$, which is exponential in the two input-size paramters n and $\log M$ (why $\log M$ and not M?).

Example 2. Solve the following 0-1 knapsack problem using a dynamic-programming approach. Assume a knapsack capacity of $M = 10$.

item	**weight**	**profit**
1	3	40
2	5	60
3	5	50
4	1	30
5	4	50

	0	1	2	3	4	5	6	7	8	9	10
0											
1											
2											
3											
4											
5											

Edit Distance Between Two Words

Given two words u and v over some alphabet, The **edit distance**, also known as **Levenshtein distance**, $d(u, v)$ is defined as the the minimum number of edit operations needed to convert one word to another. These edits include adding a character, deleting a character, and changing a character. In this lecture, each edit will be assinged a cost of 1. However, in practice, it may make more sense to assign different costs to different kinds of edits, where the more likely edits (e.g., replacing an 'e' with an 'r', as often occurs in typing errors) are given lower costs

Example 3. Compute the edit distance between the words u=sample and v=dampen.

Theorem 1. Let u and v be words, with, $|u| = m$, and $|v| = n$. For $0 \leq i \leq m$ and $0 \leq j \leq n$, define $d(i, j)$ as the edit distance between $u[1 : i]$ and $v[1 : j]$, where, e.g., $u[1 : i]$ is the prefix of word u having length i. Then

$$d(i,j) = \begin{cases} j & \text{if } i = 0 \\ i & \text{if } j = 0 \\ \min(d(i-1,j)+1, d(i,j-1)+1, d(i-1,j-1)+(u_i \neq v_j)) & \end{cases}$$

Proof of Theorem 1. Consider an optimal sequence of edits that transforms $u[1 : i]$ to $v[1 : j]$. We may assume that these edits are performed on u from right to left. Consider the first operation that is performed on u.

Case 1. The first edit in u's transformation is to add a letter to the end of u. In this case the added letter will match v_j. Hence, after adding this final letter we must now transform $u[1 : i]$ to $v[1 : j-1]$. This can be optimally done in $d(i, j-1)$ steps. Hence, adding 1 for the initial letter addition yields $d(i, j-1)+1$ steps.

Case 2. The first edit in u's transformation is to remove the last letter of u. If we are optimally transforming u to v, and the first step is to remove a letter at the end of u, then clearly this letter must be u_i. Hence, after the removal, we must subsequently transform $u[1 : i-1]$ to $v[1 : j]$. This can be optimally done in $d(i-1, j)$ steps. Hence, adding 1 for the initial letter deletion yields $d(i-1, j)+1$ steps.

Case 3. The first edit in u's transformation is to change u_i to v_j. If this is the first edit, then we must subsequently transform $u[1 : i-1]$ to $v[1 : j-1]$. The number of steps to perform this is $d(i-1, j-1)$. Hence, adding 1 for the initial letter change yields $d(i-1, j-1)+1$ steps.

Case 4. The first edit that transforms $u[1 : i]$ to $v[1 : j]$ occurs somewhere before u_i, and hence $u_i = v_j$. In this case we are actually transforming $u[1 : i-1]$ to $v[1 : j-1]$, which can be optimally performed in $d(i-1, j-1)$ steps.

Example 4. Let u = claim and v = climb. In optimally transforming u to v, what case applies for the first edit? Same question for u = gingerale and v = ginger, u = hurts and v = hertz, and u = storm and v = warm.

Notice that $d(u, v)$ can be computed by the method of dynamic programming, since the edit distance between two words is reduced to finding the edit distance between two smaller words that are prefixes of the two original words. Here the problem is to compute $d(m, n)$, and the subproblems are to compute $d(i, j)$, for each $0 \leq i \leq m$ and $0 \leq j \leq n$. The subproblems are stored in a matrix for future access. This is called **memoization**. For example, $d(3, 2)$ can be computed by comparing $d(3, 1)$, $d(2, 2)$, and $d(2, 1)$, which have all been previously stored in the matrix. This yields a total of $\Theta(mn)$ steps to compute the edit distance.

Example 5. Show the dynamic-programming matrix that is formed when computing the edit distance of $u =$ fast and $v =$ cats.

Optimal Binary Search Tree

Suppose a binary tree $\mathcal{T}$ holds keys $k_1, \ldots k_n$ (henceforth, and without loss of generality, assume that $k_i = i$). Let w_i denote a weight that is assigned to k_i. A large (respectively, small) weight means that k_i is accessed more (respectively, less) often. Now, if d_i denotes the depth of k_i (e.g. the root has depth 1), then the **weighted access cost** of $\mathcal{T}$ is defined as

$$\text{wac}(\mathcal{T}) = \sum_{i=1}^{n} w_i d_i.$$

Example 6. Suppose keys 1-5 have respective weights 50,40,20,30,40, and are inserted into an intially empty binary search tree $\mathcal{T}$ in the order 1,5,2,4,3. Determine wac($\mathcal{T}$).

Thus, the problem to be solved is to find a binary search tree that holds keys $1, \ldots, n$, and has minimal weighted access cost. The main insight that leads to a dynamic-programming recurrence for solving this problem is to observe that a binary search tree itself is a recursive structure. Moreover, consider the optimal tree T_{opt} and suppose it has root $k \in \{1, \ldots, n\}$. Let T_L and T_R denote the respective left and right subtrees of the root. Then T_L and T_R are themselves **optimal substructures**, meaning that T_L is the solution to finding a binary-search tree that has minimum weighted access cost, and which holds keys $1, \ldots, k-1$, and T_R is the solution to finding a binary-search tree that has minimum weighted access cost, and which holds keys $k+1, \ldots, n$. Suppose otherwise. For example, suppose T' is a binary search tree that holds keys $1, \ldots, k-1$, and for which $\text{wac}(T') < \text{wac}(T_L)$. Then we could replace T_L with T' in T_{opt} and obtain a binary search tree over keys $1, \ldots, n$ that has a smaller weighted access cost than T_{opt}, which is a contradiction.

The above insight suggest that we define $\text{wac}(i, j)$ as the minimum weighted access cost that can be attained by a binary search tree that holds keys $i, \ldots, j$. Then the above insight also suggests the following recurrence:

$$\text{wac}(1, n) = w_k + \text{wac}(1, k-1) + \text{wac}(k+1, n).$$

In words, the weighted access cost of T_{opt} is the cost $w_k(1)$ of accessing the root, plus the total cost of accessing keys in T_L, plus the total cost of accessing keys in T_R. But the above recurrences in not quite correct. For example the quantity $\text{wac}(1, k-1)$ makes the assumption that T_L is not a subtree of some other tree. In other words, it assumes that the root r of T_L has a depth of 1, the children of r have a depth of 2, etc.. However, since T_L is the left subtree of the root of T_{opt}, r instead has a depth of *2*, while its children have a depth of *3*, etc.. In general, if node i of T_L contributes $w_i d_i$ to $\text{wac}(1, k-1)$ then it must contribute $w_i(d_i + 1)$ when T_L is a subtree of T_{opt}. This means that an additional w_i must be added to $\text{wac}(1, k-1)$. Hence, the above recurrence must be re-written as

$$\text{wac}(1, n) = w_k + \text{wac}(1, k-1) + \sum_{r=1}^{k-1} w_r + \text{wac}(k+1, n) + \sum_{r=k+1}^{n} w_r =$$

$$\text{wac}(1, k-1) + \text{wac}(k+1, n) + \sum_{r=1}^{n} w_r.$$

Finally since, we do not know offhand which key will serve as the root to T_{opt}, we must minimize the above quantity over the different possible values of k. This leads to the following theorem.

Theorem 1. Let $\text{wac}(i, j)$ denote the minimum attainable weighted access cost for any binary search tree that holds keys $i, i+1, \ldots, j$. Then

$$\text{wac}(i, j) = \begin{cases} 0 & \text{if } j < i \\ w_i & \text{if } i = j \\ \min\limits_{i \le k \le j} (\text{wac}(i, k-1) + \text{wac}(k+1, j)) + \sum_{r=i}^{j} w_r & \text{otherwise.} \end{cases}$$

Theorem 1 provides the dynamic-programming recurrence needed to solve the Optimal Binary Search Tree problem. We must compute each entry $\text{wac}(i, j)$ of the wac matrix for all values $1 \le i \le j \le n$. It is an exercise to show that this matrix can be computed in $\Theta(n^3)$ steps.

Example 7. Use dynamic programming to determine the binary search tree of minimum weighted-access cost, and whose keys and weights are provided in Example 6.

Matrix wac

i/j	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$i=1$					
$i=2$					
$i=3$					
$i=4$					
$i=5$					

Example 7 Continued.

Matrix-Chain Multiplication

A product P of matrices is said to be **fully parenthesized** iff

- **basis step:** $P = (A)$, for some matrix A
- **inductive step:** $P = (P_1 \cdot P_2)$, where P_1 and P_2 are fully parenthesized matrix products.

Example 8. How many ways can a product of four matrices be fully parenthesized?

Given a fully parenthesized product of matrices P, the **multiplication complexity**, $mc(P)$, is defined inductively as follows.

- **basis step:** if $P = (A)$, for some matrix A, then $mc(P) = 0$.
- **inductive step:** if $P = (P_1 \cdot P_2)$, where P_1 and P_2 are fully parenthesized matrix products which respectively evaluate to $p \times q$ and $q \times r$ matrices, then

$$mc(P) = mc(P_1) + mc(P_2) + pqr.$$

Example 9. Given matrices A,B,and C with respective dimensions 10×100, 100×5, and 5×50, find $mc(A(BC))$ and $mc((AB)C)$. Conclude that the parenthesization of a product of matrices affects the multiplication complexity.

Matrix-Chain Multiplication Problem: Given a chain of matrices $A_1, \ldots, A_n$, find a full parenthesization P of the sequence for which $mc(P)$ is minimum.

Similar to the Optimal Binary Search Tree problem, we make the following key obervations about an optimal parenthesization P.

1. if $P = (A)$ for some matrix A, then $mc(P) = 0$
2. if $P = (P_1 P_2)$ where P_1 is a full parenthesization for $A_1, \ldots, A_k$ and P_2 is a full parenthesization for $A_k, \ldots, A_n$, then P_1 is the optimal parenthesization for the problem of minimizing the multiplication complexity for $A_1, \ldots, A_k$, and P_2 is the optimal parenthesization for the problem of minimizing the multiplication complexity for $A_k, \ldots, A_n$. In other words, if P is an optimal strucutre, then P_1 and P_2 are optimal substructures.

Thus, we see that the matrix-chain multiplication problem may also be solved by a bottom-up dynamic-programming algorithm, where the subproblems involve finding the optimal parenthesization of matrix sequences of the form $A_i, \ldots, A_j$. Let $p_0, p_1, \ldots, p_n$ denote the dimension sequence associated with the matrix sequence $A_1, \ldots, A_n$ (for example, A_1 is a $p_0 \times p_1$ matrix). Let $\text{mc}(i, j)$ denote the minimum multiplication complexity for the sequence $A_i, \ldots, A_j$. Let P be the optimal full parenthesization for $A_i, \ldots, A_j$. If $P = (A_i)$, then $i = j$ and $\text{mc}(i, j) = 0$. Otherwise, $P = (P_1 P_2)$ where e.g. P_1 is the optimal full parenthesization of $A_i, \ldots, A_k$, for some $i \leq k < j$. Then

$$\text{mc}(i, j) = \text{mc}(i, k) + \text{mc}(k + 1, j) + p_{i-1} p_k p_j. \tag{1}$$

We summarize as follows:

1. if $i = j$, then $\text{mc}(i, j) = 0$
2. if $i < j$, then $\text{mc}(i, j) = \min_{i \leq k < j} \{\text{mc}(i, k) + \text{mc}(k + 1, j) + p_{i-1} p_k p_j\}$

We may store the values $\text{mc}(i, j)$ in a matrix mc, and store the values k which minimize the complexity in a matrix k. For example, $s(i, j) = k$ means that k is the index which minimizes the sum in Equation 1.

Example 10. Given the five matrices below, find a full parenthesization of $A_1, \ldots, A_5$ with minimum multiplication complexity.

matrix	**dimension**
A_1	2×4
A_2	4×2
A_3	2×1
A_4	1×5
A_5	5×2

Matrix mc

i/j	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$i=1$					
$i=2$					
$i=3$					
$i=4$					
$i=5$					

Matrix k

i/j	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$i=1$					
$i=2$					
$i=3$					
$i=4$					
$i=5$					

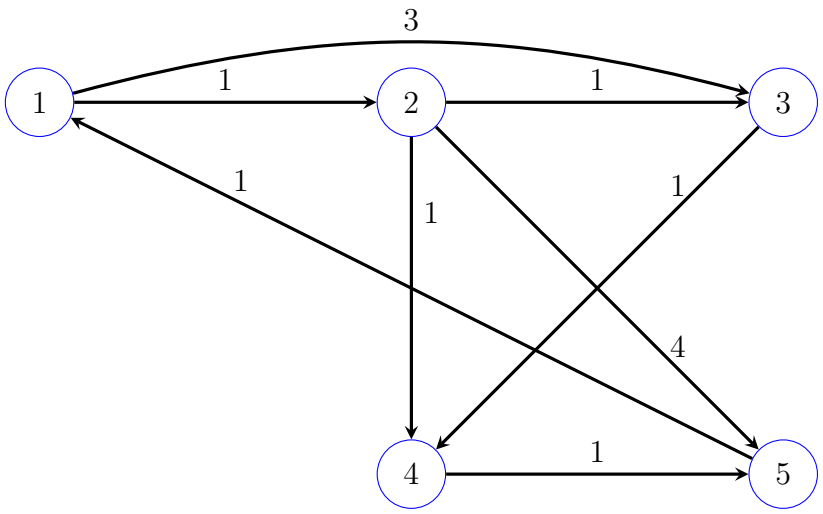
Finding Distances in a Graph

Consider the problem of finding the minimum-cost path between two vertices of a weighted graph $G = (V, E, c)$, where $c : E \to R^+$ assigns a travel cost to each edge $e \in E$. Then the cost of the path $P = e_1, e_2, \ldots, e_m$ is defined as

$$c(P) = \sum_{i=1}^{m} c(e_i).$$

Moreover, the **distance** $d(u, v)$ **between** u **and** v is defined as the cost of the path from u to v which minimizes the above sum. In other words, $d(u, v)$ is the cost of the minimum-cost path from u to v.

Example 11a. Let $G = (V, E, c)$ be the directed graph shown below. Determine the distance of each vertex from vertex 1.



A dynamic-programming recurrence for acyclic graphs

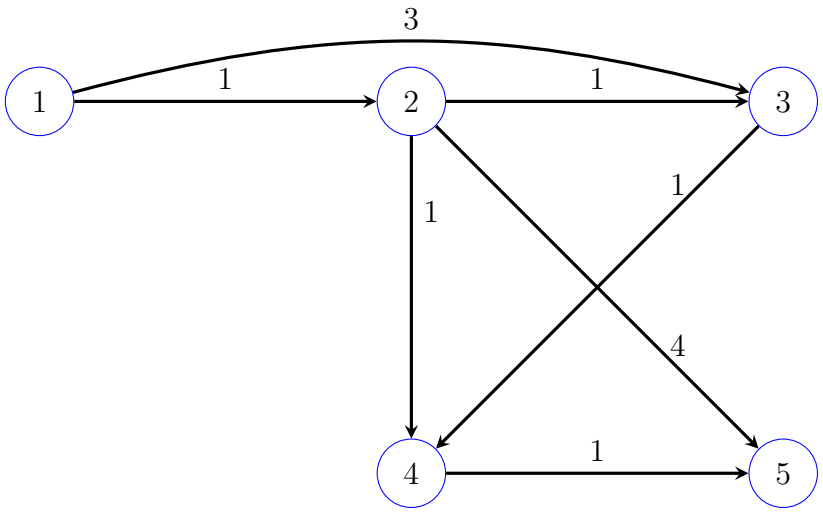
If $G = (V, E)$ is acyclic, then the single-source distances problem can be solved in linear time as opposed to log-linear using Dijkstra's algorithm. We do this using the following recurrence, where we assume that s this the source vertex.

$$d(s,v) = \begin{cases} 0 & \text{if } s = v \\ \infty & \text{if } \deg^+(v) = 0 \\ \min_{(s,u)\in E}(d(s,u) + c(u,v)) & \text{otherwise} \end{cases}$$

To efficiently use the recurrence, first perform a topological sort of all the vertices that are reachable from s. By **topological sort** we mean a linear ordering of the vertices, where, if $(u, v) \in E$, then u comes before v in the order.

Now let $s = v_0, v_1, \ldots, v_k$ be the sorted order and suppose that $d(s, v_1), \ldots, d(s, v_{j-1})$ have all been computed, then $d(s, v_j)$ may be readily computed using the above recurrence. Moreover, the number of computations is proportional to the number of edges and hence is linear in the size of the graph. Note that topologically sorting vertices may be done in linear time (Exercise!).

Example 11b. Apply the dynamic-programming recurrence for acyclic graphs to the graph shown below in order to compute the distance from vertex 1 to every other vertex.



Finding distances between all pairs of vertices

Given a graph $G = (V, E, c)$, the **all-pairs distances** problem is the problem of computing the distance $d(u, v)$, for each vertex pair $u, v \in V$.

One way of solving the all-pairs distances problem is to apply Dijkstra's algorithm n times, where the i th application of the algorithm uses vertex i as the source. This gives a worst-case running time of $\mathrm{O}(mn \log n)$, which works well in cases where $m(n) = o(n^2)$, where $m(n)$ is the number of edges as a function of the number of vertices. However, in cases where $m(n) = \Theta(n^2)$, there is a better approach known as the Floyd-Warshall algorithm.

Floyd-Warshall algorithm

We now give the Floyd-Warshall dynamic-programming algorithm for finding the distance between all pairs of graph vertices. It is based on the following simple principle. Suppose $P = u = v_0, v_1, \ldots, v_m = v$ is a minimum-cost path between vertices u and v of graph G. Then for any $0 < k < n$, the two paths

$$P_1 = u = v_0, v_1, \ldots, v_k$$

and

$$P_2 = v_k, v_{k+1}, \ldots, v_m$$

must both be minimum-cost paths. For otherwise one of them could be replaced by a minimum-cost path that would then yield a shorter distance from u to v. In other words, a minimum-cost path has optimal substructures, in that every subpath of a minimum-cost path is also a minimum-cost path. It is interesting to note that the same is *not* true for *maximum-cost* paths.

The benefit of optimal substructures in minimum-cost paths is the following. Let m be the number of edges in a minimum-cost path from vertex u to vertex v in graph G. Then there are two cases.

- **Case 1:** $m = 1$. Then the $d(u, v)$ is the cost of the edge from u to v in graph G (Note: if u is not adjacent to v, then we may assume an edge between them with a cost of ∞).
- **Case 2:** $m > 1$. Then there exists vertex w such that $d(u, v) = d(u, w) + d(w, v)$, where the lengths of the minimum-cost paths from u to w and from w to v do not exceed $m - 1$.

Now assume $\{1, 2, \ldots, n\}$ are the vertices of G, and let c_{ij} denotes the cost of the edge connecting vertex i to vertex j. The above observations suggest that we build up a minimum-cost path from u to v by piecing together two paths, each of smaller length. But rather than allowing for the "joining" vertex w to be chosen from any of the n vertices, we instead build in stages, where in stage k, $k = 1, 2, \ldots, n$, we allow for the joining vertex to be vertex k. With this in mind, we let d_{ij}^k denote the distance from vertex i to vertex j taken over all those paths whose internal vertices (i.e. vertices occuring between i and j) are a subset of $\{1, 2, \ldots, k\}$.

For $k = 0$, we set $d_{ij}^0 = c_{ij}$, if $i \neq j$, and zero otherwise. In this case d_{ij}^0 represents the distance over all paths from i to j which do not possess any internal vertices. Of course, such paths must have lengths equal to either zero (a single vertex) or one (two vertices connected by edge e_{ij} and having cost c_{ij}).

For $k > 0$ and $i \neq j$, consider d_{ij}^k and the minimum-cost path P from i to j that is restricted to using internal vertices $\{1, \ldots, k\}$. If P does not visit vertex k, then P is also a minimum-cost path from i to j that is restricted to using internal vertices $\{1, \ldots, k-1\}$. Hence, $d_{ij}^k = d_{ij}^{k-1}$. Otherwise, if P visits k, then, by the principle of optimal subpaths of an optimal path, $P = P_1 P_2$, where P_1 is a minimum-cost path from i to k, and P_2 is a minimum-cost path from k to j, where both paths

are restricted to using internal vertices $\{1, \ldots, k-1\}$. Hence, $d_{ij}^k = d_{ik}^{k-1} + d_{kj}^{k-1}$. Hence, d_{ij}^k can be computed by taking the minimum of the quantities d_{ij}^{k-1} and $d_{ik}^{k-1} + d_{kj}^{k-1}$.

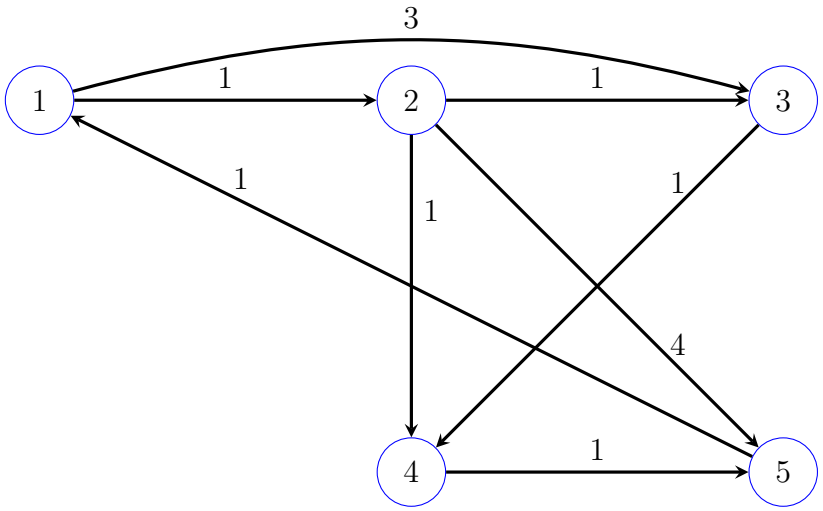
The above paragraphs are now summarized by the following dynamic-programming recurrence.

$$d_{ij}^k = \begin{cases} 0 & \text{if } i = j \\ c_{ij} & \text{if } k = 0 \\ \min(d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)}) & \text{if } k \geq 1 \end{cases}$$

Notice that d_{ij}^n gives the distance from vertex i to vertex j over all paths whose internal vertices form a subset of $\{1, 2, \ldots, n\}$, which is precisely the distance from i to j over all possible paths, and is precisely what we desired to compute. The following example provides some intuition as to why the minimum-cost path between i and j will always be constructed. In other words, the restrictions placed on the joining vertex at each stage is not detrimental to obtaining the optimal path.

Example 12. Suppose $P = 8, 6, 1, 4, 2, 5$ is a minimum-cost path. Show the order in which the Floyd-Warshall Algorithm (as implied by the dynamic-programming recurrence relation) pieces together P from smaller minimum-cost paths. For each path, indicate the k value for which the cost of the path is first recorded in d_{ij}^k.

Example 13. Run the Floyd-Warshall Algorithm on the Graph from Example 12. Show each of the matrices d_{ij}^k.



Example 13 Continued.

Exercises

1. Let f_n denote the n th Fibonacci number. If f_n has closed-form

$$f_n = c_1(\frac{1+\sqrt{5}}{2})^n + c_2(\frac{1-\sqrt{5}}{2})^n,$$

   determine the values of c_1 and c_2.

2. Prove that f_n has exponential growth. Hint: what can be say about the asymptotic growth of a sum of functions?

3. Solve the following 0-1 knapsack problem using dynamic-programming.

item	weight	profit
1	1	2
2	2	4
3	3	5
4	4	5
5	2	2
6	1	3

   with knapsack capacity 8.

4. For 0-1 knapsack, devise recursive algorithm that takes as inputs matrix $P(i, c)$, the array w of weights, the array p of profits, the number of items i, and the knapsack capacity c, and prints a list of the items that are used to obtain a profit $P(i, c)$.

5. Determine the edit distance between u = lovely and v = waver.

6. Provide the dynamic-programming matrix that is needed to efficiently compute the edit-distance between u=block and v=slacks. Circle one of the optimal paths and provide the sequence of edits that this path represents in transforming u to v.

7. Provide the dynamic-programming matrix that is needed to efficiently compute the edit-distance between u=paris and v=alice. Circle one of the optimal paths and provide the sequence of edits that this path represents in transforming u to v.

8. The Longest Common Subsequence (LCS) problem is the problem of finding the longest (non-contiguous) sequence of characters that are common to both strings u and v. For example, if u = aaccabc, and v = ababab, then aaab is the longest common subsequence. Provide a dynamic-programming recurrence for $\text{lcs}(i, j)$, the length of the longest common subsequence for $u[1 : i]$ and $v[1 : j]$. Using a matrix, apply your recurrence to the strings u = bcabac and v = abacca.

9. Suppose keys 1-5 have respective weights 30,60,10,80,50, and are inserted into an intially empty binary search tree $\mathcal{T}$ in the order 5,2,1,3,4. Determine $\text{wac}(\mathcal{T})$.

10. Use dynamic programming to determine the binary search tree of minimum weighted-access cost, and whose keys and weights are provided in the previous problem.

11. Let $K(i,j)$ denote the key of the root for the optimal bst that stores keys $i, i+1, \ldots, j$. Devise recursive Java algorithm that takes as inputs K and n (the dimension of K, and hence the number of keys in the tree) that returns an optimal bst. Use the class

```
public class BST
{
    int key;  //key value stored in the root of this BST
    BST left; //the left subtree of the root of this BST
    BST right; //the right subtree of the root fo this BST

    BST(int key,BST left, BST right); //constructor
}
```

12. Determine the running time of the Optimal Binary Search Tree dynamic programming algorithm. Hint: first determine a formula for the number of steps needed to compute $\text{wac}(i,j)$. Then sum over i and j.

13. How many ways are there to fully parenthesize a product of five matrices.

14. What is the multiplication complexity of $A(BC)$ if A has size 2×10, B has size 10×20, and C has size 20×7? Same question for $(AB)C$.

15. Use a dynamic programming algorithm to determine the minimum multiplication complexity of $A_1A_2A_3A_4A_5$, where the dimension sequence is $5, 7, 3, 9, 4, 2$.

16. Let $G = (V, E, c)$ be a directed graph, where

$$V = \{1, 2, 3, 4, 5, 6\}$$

and the directed edges-costs are given by

$$E = \{(1,5,1), (2,1,1), (2,4,2), (3,2,2), (3,6,8), (4,1,4), (4,5,3), (5,2,7), (6,2,5)\}.$$

Provide a geometical representation of graph G.

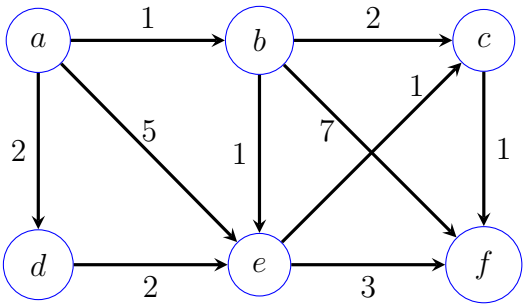
17. Find all-pairs distances for graph G in the previous problem by performing the Floyd-Warshall Algorithm. Show the matrix sequence $d^0, \ldots, d^6$.

18. Write a recursive algorithm which, on inputs $d^{(0)}$, $d^{(n)}$, i, and j, prints the sequence of vertices for a minimum-cost path from i, to j, $1 \leq i, j \leq n$, where $d^{(0)}$ is the $n \times n$ cost-adjacency matrix, while $d^{(n)}$ is the final matrix obtained from the Floyd-Warshall algorithm.

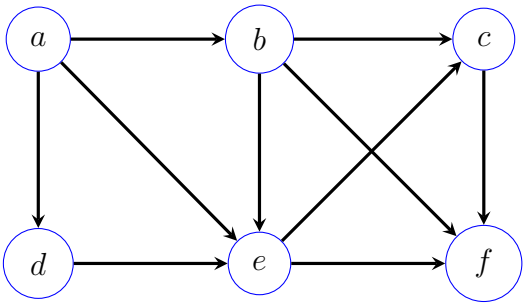
19. In the Floyd-Warshall algorithm, give a geometrical argument as to why, when computing matrix d^k, $1 \leq k \leq n$, neither row k nor column k change from $d^{(k-1)}$ to d^k.

20. Consider a simple path for a directed network that represents a *maximum-cost* path from vertex i to j. Do such paths have the optimal substructure property? Explain.

21. Use the dynamic-programming recurrence for single-source distances in an acyclic graph (see the recurrence before Example 11b) to compute $d(a, v)$, for each vertex v in the following graph. Here we assume that a is the source.



22. Use a variation of the dynamic-programming recurrence for single-source distances in an acyclic graph (see the recurrence before Example 11b) to compute the *longest path* from source a to all other vertices. Provide the modified recurrence and apply it to the following graph. Hint: we are assuming that all edge costs equal 1.



23. Given an array of n integers, the problem is to determine the longest increasing subsequence of integers in that array. Note: the sequence does not necessarily have to be contiguous. Show how the previous problem can be used to solve this problem, by constructing the appropriate graph. Hint: the vertices of the graph should consist of the n integers.

24. A production plant has two assembly lines. Each line has 3 stations. Matrix

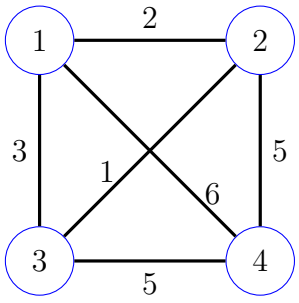
$$A = \begin{pmatrix} 3 & 5 & 6 \\ 4 & 2 & 7 \end{pmatrix}$$

is a 2×3 matrix for which a_{ij} gives the processing times for an item that is being assembled at station j of line i. When an item finishes stage $j < 3$ of line i, it has the option of either remaining on line i and proceeding to stage $j + 1$, or moving to the other line, and then proceeding to stage $j + 1$. If it chooses to stay on the same line, then it requires 0.5 units of time to move to the next station. Otherwise it requires 2 units of time to move to the next station located on the other line. Show how this problem can be reduced to finding the distance between two vertices in an acyclic graph. Draw the graph and apply the single source distances recurrence for acyclic graphs to determine the "distance" (i.e. minimum processing time) and optimal path through the assembly plant.

25. Given n cities, let C be an $n \times n$ matrix whose C_{ij} entry represents the cost in traveling from city i to city j. Determine a dynamic-programming recurrence relation that will allow one to determine a minimum-cost tour that begins at city 1 and visits every other city exactly once.

Hint: let $\text{mc}(i, A)$ denote the minimum-cost tour that begins at city i and visits every city in A which is a subset of the cities, and does not include i. Determine a recurrence for $\text{mc}(i, A)$.

26. Apply the recurrence from the previous exercise to the following graph. Again, assume the tour begins at 1.



Solutions to Exercises

1. $\pm\sqrt{5}/5$

2. Prove that $f_n = \Theta((\frac{1+\sqrt{5}}{2})^n)$

3.

x_i, c	0	1	2	3	4	5	6	7	8
x_1	0	2	2	2	2	2	2	2	2
x_2	0	2	4	6	6	6	6	6	6
x_3	0	2	4	6	7	9	11	11	11
x_4	0	2	4	6	7	9	11	11	12
x_5	0	2	4	6	7	9	11	11	13
x_6	0	3	5	7	9	10	12	14	14

4.
```
void print_items(Matrix P, int[] w, int[] p, int i, int c)
{
     //base case
     if(i == 0 || c == 0)
          return;

     if(P[i-1,c] != P[i,c])
     {
          print_items(P, w, p,i-1,c-w[i]);
          print i;
          return;
     }

     print_items(P, w, p,i-1,c);
}
```

5. 4

6. In matrix, "l" stands for left, "u" for up, and "d" for diagonal.

	λ	s	l	a	c	k	s
λ	0	1,l	2,l	3,l	4,l	5,l	6,l
b	1,u	1,d	2,ld	3,ld	4,ld	5,ld	6,ld
l	2,u	2,du	1,d	2,l	3,l	4,l	5,l
0	3,u	3,du	2,u	2,d	3,ld	4,ld	5,ld
c	4,u	4,du	3,u	3,du	2,d	3,l	4,l
k	5,u	5,du	4,u	4,du	3,u	2,d	3,l

   Optimal transformation: $b \to s$, $o \to a$, $+s$

7. In matrix, "l" stands for left, "u" for up, and "d" for diagonal.

	λ	a	l	i	c	e
λ	0	1,l	2,l	3,l	4,l	5,l
p	1,u	1,d	2,ld	3,ld	4,ld	5,ld
a	2,u	1,d	2,ld	3,ld	4,ld	5,ld
r	3,u	2,u	2,d	3,ld	4,ld	5,ld
i	4,u	3,u	3,du	2,d	3,l	4,l
s	5,u	4,u	4,du	3,u	3,d	4,ld

Optimal transformation: $-p$, $r \to l$, $s \to c$, $+e$

8. If either u or v is empty, then $\text{lcs}(i,j) = 0$. Now suppose both u and v are nonempty and $u_i \neq v_j$. In this case the lcs either does not use u_i or does not use v_j (why?). Thus, we get the recurrence $\text{lcs}(i,j) = \max(\text{lcs}(i-1,j), \text{lcs}(i,j-1))$. Finally, if $u_i = v_j$, then the lcs must end with u_i (why?), and we may assume that either u_i or v_j (or both) is used in constructing the lcs. Hence, $\text{lcs}(i,j) = \text{lcs}(i-1,j-1) + 1$. Putting all the above together, we get the following recurrence.

$$\text{lcs}(i,j) = \begin{cases} 0 & \text{if } i = 0 \text{ or } j = 0 \\ \max(\text{lcs}(i-1,j), \text{lcs}(i,j-1)) & \text{if } u_i \neq v_j \\ \text{lcs}(i-1,j-1) + 1 & \text{otherwise} \end{cases}$$

Using the matrix below, we find that the lcs for strings u = bcabac and v = abacca equals abac.

	λ	a	b	a	c	c	a
λ	0	0	0	0	0	0	0
b	0	0,lu	1,d	1,l	1,l	1,l	1,l
c	0	0,lu	1,u	1,lu	2,d	2,d	2,l
a	0	1,d	1,lu	2,d	2,lu	2,lu	3,d
b	0	1,u	2,d	2,lu	2,lu	2,lu	3,u
a	0	1,d	2,u	3,d	3,l	3,l	3,d
c	0	1,u	2,u	3,u	4,d	4,d	4,l

9. $\text{wac}(\mathcal{T}) = 50 + (2)(60) + 3(30+10) + (4)(80) = 610$

10. Entries of the form $\text{wac}(i,j)/k$ give the optimal weighted access cost , followed by the root k of the corresponding optimal tree.

i/j	1	2	3	4	5
1	30	120/2	140/2	310/2	420/4
2	0	60	80/2	230/4	330/4
3	0	0	10	100/4	200/4
4	0	0	0	80	180/4
5	0	0	0	0	50

The optimal tree root has key 4, while the optimal left sub-tree has root key 2.

11.
```
BST optimal_bst(Matrix K, int i, int j)
{
     if(i==j)
         return new BST(i,null,null)
```

```
        int k = K[i,j];
        return new BST(k,optimal_bst(K,i,k-1),optimal_bst(K,k+1,j);
    }
```

12. $\Theta(n^3)$. Ciomputing entry (i, j) requires $\Theta(j - i + 1)$ steps. Hence, the running time is proportional to $\sum_{i=1}^{n} \sum_{j=i}^{n} (j - i + 1)$. Moreover, using basic summation formulas (see the exercises from the Big-O lecture), one can show that this sum is $\Theta(n^3)$.

13. 14

14. $A(BC)$: 1540, $(AB)C$: 680

15. Each entry is of the form $m(i, j), k$

i/j	1	2	3	4	5
1	0	105	240/2	273/2	238/1
2	0	0	189	192/2	168/2
3	0	0	0	108	126/3
4	0	0	0	0	72
5	0	0	0	0	0

16. (a, b, c) means the directed edge incident with a and b, and having cost c.

17.
$$d^0 = \begin{pmatrix} 0 & \infty & \infty & \infty & 1 & \infty \\ 1 & 0 & \infty & 2 & \infty & \infty \\ \infty & 2 & 0 & \infty & \infty & 8 \\ 4 & \infty & \infty & 0 & 3 & \infty \\ \infty & 7 & \infty & \infty & 0 & \infty \\ \infty & 5 & \infty & \infty & \infty & 0 \end{pmatrix}$$

$$d^2 = \begin{pmatrix} 0 & \infty & \infty & \infty & 1 & \infty \\ 1 & 0 & \infty & 2 & 2 & \infty \\ 3 & 2 & 0 & 4 & 4 & 8 \\ 4 & \infty & \infty & 0 & 3 & \infty \\ 8 & 7 & \infty & 9 & 0 & \infty \\ 6 & 5 & \infty & 7 & 7 & 0 \end{pmatrix}$$

$d^3 = d^2$ (why?) $d^4 = d^3$.

$$d^5 = \begin{pmatrix} 0 & 8 & \infty & 10 & 1 & \infty \\ 1 & 0 & \infty & 2 & 2 & \infty \\ 3 & 2 & 0 & 4 & 4 & 8 \\ 4 & 10 & \infty & 0 & 3 & \infty \\ 8 & 7 & \infty & 9 & 0 & \infty \\ 6 & 5 & \infty & 7 & 7 & 0 \end{pmatrix}$$

$d^5 = d^6$ (why?)

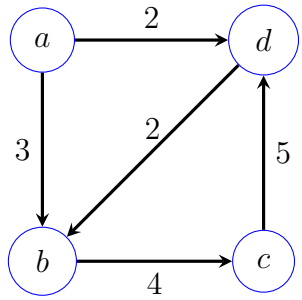
18.
```
void print_optimal_path(Matrix d0, Matrix dn, int n, int i, int j)
{
    if(d0[i,j]==dn[i,j]])//optimal path is a direct connection
    {
        print i + " " + j;
        return;
    }

    //optimal path has a final intermediate vertex k. Find k
    int k;

    for(k = 1; k <= n; k++)
    {
        if(k != j && dn[i,k]+d0[k,j] == dn[i,j])//found parent k
        {
            print_optimal_path(d0,dn,n,i,k);
            print " " + j;
        }
    }
}
```

19. Row k represents distances from k, while column k represents distances to k. Thus, none of these distances can improve when allowing k to be an intermediate vertex, since the optimal paths either begin or end at k.

20. See the graph below. $P = a, b, c, d$ is a maximum-cost simple path from a to d, but $P^{`} = a, b$ is *not* a maximum-cost path from a to b. Hence, maximum-cost simple paths do not possess optimal substructures.



21. Start with the source, then proceed to the next vertex v for which $d(a, u)$ has already been computed, for each parent u of v.

$$d(a, a) = 0.$$

$$d(a, b) = d(a, a) + 1 = 1.$$

$$d(a, d) = d(a, a) + 2 = 2.$$

$$d(a, e) = \min(d(a, a) + 5, d(a, b) + 1, d(a, d) + 2) = 2.$$

$$d(a, c) = \min(d(a, b) + 2, d(a, e) + 1) = 3.$$

$$d(a, f) = \min(d(a, b) + 7, d(a, c) + 1, d(a, e) + 3) = 4.$$

22.

$$l(a,v) = \begin{cases} 0 & \text{if } a = v \\ \infty & \text{if } \deg^+(v) = 0 \\ \max\limits_{(u,v)\in E}(l(a,u)) + 1 & \text{otherwise} \end{cases} \quad 1$$

$$l(a,a) = 0.$$

$$l(a,b) = l(a,a) + 1 = 1$$

$$l(a,d) = l(a,a) + 1 = 1$$

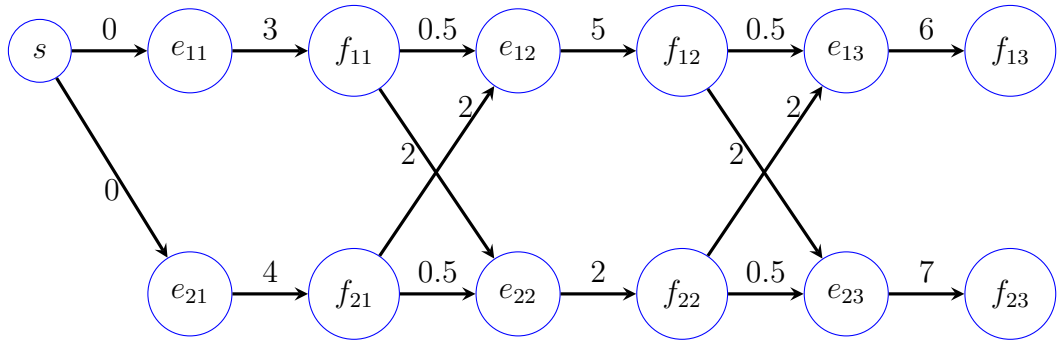
$$l(a,e) = \max(l(a,a), l(a,b), l(a,d)) + 1 = 2.$$

$$l(a,c) = \max(l(a,b), l(a,e)) + 1 = 3.$$

$$l(a,f) = \max(l(a,b), l(a,c), l(a,e)) + 1 = 4.$$

23. Define the directed graph $G = (V, E)$ so that V is the set of integers and $(m, n) \in E$ iff $m \leq n$ and m appears before n in the array. Then the longest increasing subsequence corresponds with the longest path of G.

24. Define a weighted directed acyclic graph as follows for each station S_{ij} define nodes e_{ij} and f_{ij}, where e_{ij} denotes the entry point to S_{ij}, and f_{ij} denotes its finish point. Add the edge (e_{ij}, f_{ij}) and give it weight a_{ij}, the time needed to process an item at S_{ij}. Next, for each node f_{ij}, $j < 3$, add the edges $(f_{ij}, e_{i(j+1)}, 0.5)$, $(f_{ij}, e_{i'(j+1)}, 2)$, where $i' = 2$ if $i = 1$, and $i' = 1$ if $i = 2$. Finally, add source vertex s and connect it to both e_{11} and e_{21} using 0-weight edges. The graph for the production-plant assembly lines is shown below. The least processing time can now be found by computing the minimum of $d(f_{13})$ and $d(f_{23})$.



25. Let $\text{mc}(i, A)$ denote the minimum-cost tour that begins at city i and visits every city in A, where A is a subset of cities that does not include i. Then

$$\text{mc}(i, A) = \begin{cases} 0 & \text{if } A = \emptyset \\ C_{ij} & \text{if } A = \{j\} \\ \min\limits_{j\in A}(C_{ij} + \text{mc}(j, A - \{j\}) & \text{otherwise} \end{cases}$$

26. Start with $\text{mc}(1, \{2, 3, 4\})$ and proceed to compute other mc values as needed.

$$\text{mc}(1, \{2,3,4\}) = \min(2 + \text{mc}(2, \{3,4\}), 3 + \text{mc}(3, \{2,4\}), 6 + \text{mc}(4, \{2,3\})).$$

$$\text{mc}(2, \{3,4\}) = \min(1 + \text{mc}(3, \{4\}), 5 + \text{mc}(4, \{3\})) = \min(1 + 5, 5 + 5) = 6.$$

$$\mathrm{mc}(3, \{2, 4\}) = \min(1 + \mathrm{mc}(2, \{4\}), 5 + \mathrm{mc}(4, \{2\})) = \min(1 + 5, 5 + 5) = 6.$$

$$\mathrm{mc}(4, \{2, 3\}) = \min(5 + \mathrm{mc}(2, \{3\}), 5 + \mathrm{mc}(3, \{2\})) = \min(5 + 1, 5 + 1) = 6.$$

Therefore,

$$\mathrm{mc}(1, \{2, 3, 4\}) = \min(2 + \mathrm{mc}(2, \{3, 4\}), 3 + \mathrm{mc}(3, \{2, 4\}), 6 + \mathrm{mc}(4, \{2, 3\})) =$$

$$\min(2 + 6, 3 + 6, 6 + 6) = 8.$$