

At the beginning of each iteration of the loop of lines 3-6, for any array index k ,

- If $p \leq k \leq i$, then $A[k] \leq x$.
- If $i+1 \leq k \leq j-1$, then $A[k] > x$.
- If $k = r$, then $A[k] = x$.

Initialization: Prior to the first iteration of the loop, $i = p-1$ and $j = p$. Because no values lie between p and j and no values lie between $i+1$ and $j-1$, the first two conditions of the loop invariant are trivially satisfied. The assignment in line 1 satisfies the third condition.

Maintenance: As Figure 7.3 shows, we consider two cases, depending on the outcome of the test in line 4. Figure 7.3(a) shows what happens when $A[j] > x$; the only action in the loop is to increment j . After j is incremented, condition 2 holds for $A[j-1]$ and all other entries remain unchanged. Figure 7.3(b) shows what happens when $A[j] \leq x$; the loop increments i , swaps $A[j]$ and $A[i]$, and then increments j . Because of the swap, we now have that $A[i] \leq x$, and condition 1 is satisfied. Similarly, we also have that $A[j-1] > x$, since the item that was swapped into $A[j-1]$ is, by the loop invariant, greater than x .

Termination: At termination, $j = r$. Therefore, every entry in the array is in one of the three sets described by the invariant, and we have partitioned the values in the array into three sets: those less than or equal to x , those greater than x , and a singleton set containing x .

Dynamic-programming:

BOTTOM-UP-CUT-ROD(p, n)

```
1 let  $r[0..n]$  be a new array
2  $r[0] = 0$ 
3 for  $j = 1$  to  $n$ 
4    $q = -\infty$ 
5   for  $i = 1$  to  $j$ 
6      $q = \max(q, p[i] + r[j-i])$ 
7    $r[j] = q$ 
8 return  $r[n]$ 
```

time complexity is $O(n^2)$, when each cut incurs a fixed cost of c , we need to change line 6 into: $q = \max(q, p[i] + r[j-1] - c)$ and line 5, for $i=1$ to $j-1$, since we might make no cuts, and modify line 4, $q = p[j]$

Egg-dropping:

```
# Function to get minimum number of trials needed in worst
# case with  $n$  eggs and  $k$  floors
def eggDrop(n, k):
    # A 2D table where entry eggFloor[i][j] will represent minimum
    # number of trials needed for  $i$  eggs and  $j$  floors.
    eggFloor = [[0 for x in range(k+1)] for x in range(n+1)]

    # We need one trial for one floor and 0 trials for 0 floors
    for i in range(1, n+1):
        eggFloor[i][1] = 1
        eggFloor[i][0] = 0

    # We always need  $j$  trials for one egg and  $j$  floors.
    for j in range(1, k+1):
        eggFloor[1][j] = j

    # Fill rest of the entries in table using optimal substructure
    # property
    for i in range(2, n+1):
        for j in range(2, k+1):
            eggFloor[i][j] = INT_MAX
            for x in range(1, j+1):
                res = 1 + max(eggFloor[i-1][x-1], eggFloor[i][j-x])
                if res < eggFloor[i][j]:
                    eggFloor[i][j] = res

    # eggFloor[n][k] holds the result
    return eggFloor[n][k]
```

time $T(n) = O(nk^2)$ space $= O(nk)$

longest increasing subsequence:

```
# Dynamic programming Python implementation of LIS problem
# This returns length of the longest increasing subsequence
def lis(arr):
    n = len(arr)

    # Declare the list (array) for LIS and initialize LIS
    # values for all indexes
    lis = [1]*n

    # Compute optimized LIS values in bottom up manner
    for i in range(1, n):
        for j in range(0, i):
            if arr[i] > arr[j] and lis[i] < lis[j] + 1:
                lis[i] = lis[j] + 1

    # Initialize maximum to 0 to get the maximum of all
    # LIS
    maximum = 0

    # Pick maximum of all LIS values
    for i in range(n):
        maximum = max(maximum, lis[i])

    return maximum
# end of lis function
```

time $T(n) = O(n^2)$

knapsack problem:

```
# A Dynamic Programming based Python Program for 0-1 Knapsack problem
# Returns the maximum value that can be put in a knapsack of capacity  $W$ 
def knapsack(W, wt, val, n):
    K = [[0 for x in range(W+1)] for x in range(n+1)]

    # Build table  $K[][]$  in bottom up manner
    for i in range(n+1):
        for w in range(W+1):
            if i==0 or w==0:
                K[i][w] = 0
            elif wt[i-1] <= w:
                K[i][w] = max(val[i-1] + K[i-1][w-wt[i-1]], K[i-1][w])
            else:
                K[i][w] = K[i-1][w]

    return K[n][W]
```

time $T(n) = O(nW)$ n : the number of items and W is the capacity of knapsack.

Find sum in a given set:

```
def isSubSum(s, n, sm):
    # The value of subset[i][j] will be
    # true if there is a subset of
    # set[0..j-1] with sum equal to i
    boolean[ ][ ] solution = new boolean[A.length + 1][sum + 1]

    # If sum is 0, then answer is true
    for i in range(0, n + 1):
        subset[i][0] = True

    # If sum is not 0 and set is empty,
    # then answer is false
    for i in range(1, sm + 1):
        subset[0][i] = False

    # Fill the subset table in bottom
    # up manner
    for i in range(1, n + 1):
        for j in range(1, sm + 1):
            if j <= s[i-1]:
                subset[i][j] = subset[i-1][j]
            if j >= s[i-1] and subset[i-1][j] == False:
                subset[i][j] = subset[i-1][j] or subset[i-1][j - s[i-1]]

    return subset[n][sm]
```

	Sum						
	0	1	2	3	4	5	6
0	T	F	F	F	F	F	F
1	T	T	F	F	F	F	F
2	T	T	T	F	T	F	F
3	T	T	T	T	F	T	F
4	T	T	T	T	T	T	T

Time $T(n) = O(\text{SUM} * n)$ where n is elements.

Longest common subsequence:

```
LCS-LENGTH( $X, Y$ )
1  $m = X.length$ 
2  $n = Y.length$ 
3 let  $b[1..m, 1..n]$  and  $c[0..m, 0..n]$  be new tables
4 for  $i = 1$  to  $m$ 
5    $c[i, 0] = 0$ 
6 for  $j = 0$  to  $n$ 
7    $c[0, j] = 0$ 
8 for  $i = 1$  to  $m$ 
9   for  $j = 1$  to  $n$ 
10    if  $x_i == y_j$ 
11       $c[i, j] = c[i-1, j-1] + 1$ 
12    else  $c[i, j] = \infty$ 
13  else if  $x_i < y_j$ 
14     $c[i, j] = c[i-1, j]$ 
15  else  $c[i, j] = c[i, j-1]$ 
16  else  $c[i, j] = c[i, j-1]$ 
17   $b[i, j] = \leftarrow$ 
18 return  $c$  and  $b$ 
```

Theorem 15.1 (Optimal substructure of an LCS)

Let $X = \langle x_1, x_2, \dots, x_m \rangle$ and $Y = \langle y_1, y_2, \dots, y_n \rangle$ be sequences, and let $Z = \langle z_1, z_2, \dots, z_k \rangle$ be any LCS of X and Y .

- If $x_m = y_n$, then $z_k = x_m$ and Z_{k-1} is an LCS of X_{m-1} and Y_{n-1} .
- If $x_m \neq y_n$, then $z_k \neq x_m$ implies that Z is an LCS of X_{m-1} and Y .
- If $x_m \neq y_n$, then $z_k \neq y_n$ implies that Z is an LCS of X and Y_{n-1} .

Proof (1) If $z_k \neq x_m$, then we could append $x_m = y_n$ to Z to obtain a common subsequence of X and Y of length $k+1$, contradicting the supposition that Z is a longest common subsequence of X and Y . Thus, we must have $z_k = x_m = y_n$. Now, the prefix Z_{k-1} is a length- $(k-1)$ common subsequence of X_{m-1} and Y_{n-1} . We wish to show that it is an LCS. Suppose for the purpose of contradiction that there exists a common subsequence W of X_{m-1} and Y_{n-1} with length greater than $k-1$. Then, appending $x_m = y_n$ to W produces a common subsequence of X and Y whose length is greater than k , which is a contradiction. (2) If $z_k \neq x_m$, then Z is a common subsequence of X_{m-1} and Y . If there were a common subsequence W of X_{m-1} and Y with length greater than k , then W would also be a common subsequence of x_m and Y , contradicting the assumption that Z is an LCS of X and Y . (3) The proof is symmetric to (2).

	j	0	1	2	3	4	5	6
i	y_j	B	D	C	A	B	A	
0	x_i	0	0	0	0	0	0	
1	A	0	↑	↑	↑	↑	↑	
2	B	0	↑	↑	↑	↑	↑	
3	C	0	↑	↑	↑	↑	↑	
4	B	0	↑	↑	↑	↑	↑	
5	D	0	↑	↑	↑	↑	↑	
6	A	0	↑	↑	↑	↑	↑	
7	B	0	↑	↑	↑	↑	↑	

DYNAMIC_ACTIVITY_SELECTOR(S):

```
initialize  $c[i, j] = 0$ 
for  $i < -1$  to  $n$ 
  do for  $j < -2$  to  $n$ 
    do if  $i >= j$ 
      then  $c[i, j] <- 0$ 
    else
      for  $k < -i+1$  to  $j-1$ 
        do if  $c[i, j] < c[i, k] + c[k, j] + 1$ 
          then  $c[i, j] <- c[i, k] + c[k, j] + 1$ 
           $s[i, j] <- k$ 
```

$T(n) = O(n^3)$

BELLMAN-FORD(G, w, s)

```
1 INITIALIZE-SINGLE-SOURCE( $G, s$ )
2 for  $i = 1$  to  $|G.V| - 1$ 
3   for each edge  $(u, v) \in G.E$ 
4     RELAX( $u, v, w$ )
5 for each edge  $(u, v) \in G.E$ 
6   if  $v.d > u.d + w(u, v)$ 
7     return FALSE
8 return TRUE
```

RELAX(u, v, w)

```
1 if  $v.d > u.d + w(u, v)$ 
2    $v.d = u.d + w(u, v)$ 
3    $v.\pi = u$ 
```

DIJKSTRA(G, w, s)

```
1 INITIALIZE-SINGLE-SOURCE( $G, s$ )
2  $S = \emptyset$ 
3  $Q = G.V$ 
4 while  $Q \neq \emptyset$ 
5    $u = \text{EXTRACT-MIN}(Q)$ 
6    $S = S \cup \{u\}$ 
7   for each vertex  $v \in G.Adj[u]$ 
8     RELAX( $u, v, w$ )
```

Let $X = \{x_1, x_2, \dots, x_k\}$, we sort and re-label the points so that $x_1 \leq x_2 \leq \dots \leq x_k$. Let S_j be the smallest set of intervals we build (the solution), contains some intervals $I_k = [x_k, x_k + 1]$, where $i \leq k \leq j$. Same definition for S_j and S_k . $X_k = S_k \cap X$, $X_k = S_k \cap X$, S_k is the optimal solution for sub-problem X_k , S_j is the optimal solution for sub-problem X_k .

B, Consider any nonempty sub-problem X_k and let x_1 be a point in X_k with the smallest position. Then interval $I_1 = [x_1, x_1 + 1]$ is included in some of smallest set of intervals of X_k . $I_1' = [x_1', x_1' + 1]$, and $I_1 = [x_1, x_1 + 1]$. If $x_1' < x_1$, we can say S_k is not a solution for the question since the first point x_1 isn't included in S_k . If $x_1' < x_1$, as x_1 is the leftmost point, there are no points from X_k contained in the interval $[x_1', x_1]$. Therefore, we could simply replace the interval $[x_1', x_1 + 1]$ in S_k (which is S_{k-1}) with the interval $[x_1, x_1 + 1]$ such that the new set of intervals $S_{k-1, \text{revise}}$ is still optimal as $|S_k| = |S_{k-1, \text{revise}}|$ and all points are covered.

```
def Unit_length_closed_intervals(s, X):
    new_x = list()
    if len(X) == 0:
        return s
    else:
        X.sort()
        first_point = X[0]
        #print(first_point)
        answer = [first_point, first_point+1]
        s.append(answer)

        for i in range(0, len(X)):
            if X[i] <= (first_point+1):
                continue
            else:
                new_x.append(X[i])
        return Unit_length_closed_intervals(s, new_x)

X=[6,1,12,3,14,5,5,3,4,5,5,1,3,2,1]

s = []
Unit_length_closed_intervals(s,X)
print(s)

def Unit_length_closed_intervals_Iterative(s, X):
    X.sort()

    while len(X) != 0:
        #print (i)
        #print (s)
        new_x = list()
        for i in range(0, len(X)):
            if X[i] <= (first_point + 1):
                continue
            else:
                new_x.append(X[i])
        X = new_x
        answer = [first_point, first_point+1]
        s.append(answer)

    return s

X=[6,1,12,3,14,5,5,3,4,5,5,1,3,2,1]

s = []
s2 = []
Unit_length_closed_intervals(s2,X)
print(s2)
Unit_length_closed_intervals_Iterative(s,X)
print(s)

Unit_length_clo... while len(X) != 0
```

RECURSIVE-ACTIVITY-SELECTOR(s, f, k, n)

```
1  $m = k + 1$ 
2 while  $m \leq n$  and  $s[m] < f[k]$  // find the first activity in  $S_k$  to
3    $m = m + 1$ 
4 if  $m \leq n$ 
5   return  $\{a_m\} \cup \text{RECURSIVE-ACTIVITY-SELECTOR}(s, f, m, n)$ 
6 else return  $\emptyset$ 
```

Huffman-coding:

Steps to build Huffman Tree

Input is array of unique characters along with their frequency of occurrences and output is Huffman Tree.

- Create a leaf node for each unique character and build a min heap of all leaf nodes (Min Heap is used as a priority queue. The value of frequency field is used to compare two nodes in min heap. Initially, the least frequent character is at root).
- Extract two nodes with the minimum frequency from the min heap.
- Create a new internal node with frequency equal to the sum of the two nodes frequencies. Make the first extracted node as its left child and the other extracted node as its right child. Add this node to the min heap.
- Repeat steps 2 and 3 until the heap contains only one node. The remaining node is the root node and the tree is complete.

HUFFMAN(C)

```
1  $n = |C|$ 
2  $Q = C$ 
3 for  $i = 1$  to  $n - 1$ 
4   allocate a new node  $z$ 
5    $z.\text{left} = x = \text{EXTRACT-MIN}(Q)$ 
6    $z.\text{right} = y = \text{EXTRACT-MIN}(Q)$ 
7    $z.\text{freq} = x.\text{freq} + y.\text{freq}$ 
8   INSERT( $Q, z$ )
9 return EXTRACT-MIN( $Q$ ) // return
```

Bellman:

BELLMAN-FORD(G, w, s)

```
1 INITIALIZE-SINGLE-SOURCE( $G, s$ )
2 for  $i = 1$  to  $|G.V| - 1$ 
3   for each edge  $(u, v) \in G.E$ 
4     RELAX( $u, v, w$ )
5 for each edge  $(u, v) \in G.E$ 
6   if  $v.d > u.d + w(u, v)$ 
7     return FALSE
8 return TRUE
```

RELAX(u, v, w)

```
1 if  $v.d > u.d + w(u, v)$ 
2    $v.d = u.d + w(u, v)$ 
3    $v.\pi = u$ 
```

DIJKSTRA(G, w, s)

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1 INITIALIZE-SINGLE-SOURCE( $G, s$ )
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3  $Q = G.V$ 
4 while  $Q \neq \emptyset$ 
5    $u = \text{EXTRACT-MIN}(Q)$ 
6    $S = S \cup \{u\}$ 
7   for each vertex  $v \in G.Adj[u]$ 
8     RELAX( $u, v, w$ )
```

Suppose that we have a set of activities to schedule among a large number of lecture halls, where any activity can take place in any lecture hall. We wish to schedule all the activities using as few lecture halls as possible. Give an efficient greedy algorithm to determine which activity should use which lecture hall.

Maintain a set of free (but already used) lecture halls F and currently busy lecture halls B . Sort the classes by start time. For each new start time which you encounter, remove a lecture hall from F , schedule the class in that room,

and add the lecture hall to B . If F is empty, add a new, unused lecture hall to F . When a class finishes, remove its lecture hall from B and add it to F . Why this is optimal: Suppose we have just started using the m^{th} lecture hall for the first time. This only happens when ever classroom ever used before is in B . But this means that there are m classes occurring simultaneously, so it is necessary to have m distinct lecture halls in use.

16.1-5

Consider a modification to the activity-selection problem in which each activity a_i has, in addition to a start and finish time, a value v_i . The objective is no longer to maximize the number of activities scheduled, but instead to maximize the total value of the activities scheduled. That is, we wish to choose a set A of compatible activities such that $\sum_{a_i \in A} v_i$ is maximized. Give a polynomial-time algorithm for this problem.

$$c[i, j] = \begin{cases} 0 & \text{if } S_j = \emptyset \\ \max_{a_k \in S_j} \{c[i, k] + c[k, j] + 1\} & \text{if } S_j \neq \emptyset \end{cases} \quad (16.2)$$

Run a dynamic programming solution based off of the equation (16.2) where the second case has " \leftarrow " replaced with " $=$ ". Since the subproblems are still induced by a pair of activities, and such calculation requires taking the minimum over some set of size $\leq |S_j| \in O(n)$. The total runtime is bounded by $O(n^3)$.

just change value of 1 into V_k in the left corner.

DYNAMIC-ACTIVITY-SELECTOR(s, f, n)

```
let  $c[0..n+1, 0..n+1]$  and  $act[0..n+1, 0..n+1]$ 
for  $i = 0$  to  $n$ 
   $c[i, i] = 0$ 
```

```
 $c[i, i+1] = 0$ 
 $c[n+1, n+1] = 0$ 
for  $i = 2$  to  $n+1$ 
  for  $j = 0$  to  $n-i+1$ 
     $j = i+1$ 
     $c[i, j] = 0$ 
     $k = j-1$ 
    while  $f[i] < f[k]$ 
      if  $f[i] < s[k]$  and  $f[k] <= s[j]$ 
        and  $c[i, k] + c[k, j] + 1 > c[i, j]$  do
           $c[i, j] = c[i, k] + c[k, j] + 1$ 
           $act[i, j] = k$ 
     $k = k-1$ 
    print "A max size set of mutually compatible activities "
    print  $c[i, n+1]$ 
    print "The set contains "
    PRINT-ACTIVITIES( $c, act, 0, n+1$ )

PRINT-ACTIVITIES( $c, act, i, j$ )
  if  $c[i, j] > 0$ 
     $k = act[i, j]$ 
    print  $k$ 
    PRINT-ACTIVITIES( $c, act, i, k$ )
    PRINT-ACTIVITIES( $c, act, k, j$ )
```

We create two fictitious activities, a_0 with $f_0 = 0$ and a_{n+1} with $s_{n+1} = \infty$. We are interested in a maximum-size set $A_{0, n+1}$ of mutually compatible activities in $S_{0, n+1}$. We'll use tables $c[0..n+1, 0..n+1]$ as in recurrence (16.2) (so that $c[i, j] = |A_{i, j}|$) and $act[0..n+1, 0..n+1]$, where $act[i, j]$ is the activity k that we choose to put into $A_{i, j}$.

We fill the tables in according to increasing difference $j-i$, which we denote by l in the pseudocode. Since $S_j = \emptyset$ if $j-i < 2$, we initialize $c[i, j] = 0$ for all i and $c[i, i+1] = 0$ for $0 \leq i \leq n$. As in RECURSIVE-ACTIVITY-SELECTOR and GREEDY-ACTIVITY-SELECTOR, the start and finish times are given as arrays s and f , where we assume that the arrays already include the two fictitious activities and that the activities are sorted by monotonically increasing finish time.

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