Solutions for Homework Assignment #6

Answer to Question 1.

a. Suppose we have three orders with the deadlines, lengths, and profits indicated in the able below:

i	d_i	$\mid \ell_i \mid$	p_i
1	2	2	1.1
2	2	1	1
3	2	1	1

The greedy algorithm would schedule only order 1, for a total profit of 1.1, whereas we can schedule jobs 2 and 3 for a total profit of 2.

b. <u>Definition of the subproblems that our dynamic programming algorithm will solve:</u> Without loss of generality, assume that $d_1 \leq d_2 \leq \ldots \leq d_n$ (rename the orders, if needed — the order is important for the recursive formula). For each $i, 0 \leq i \leq n$, and each $i, 0 \leq i \leq n$, and each $i, 0 \leq i \leq n$.

$$P(i,t) =$$
 the maximum profit achievable to schedule a subset of orders 1.. i so that they all finish by time t (*)

Recursive formula to compute each subproblem: Let $t' \ni \min(t, d_i)$; this represents the latest time by which order i must finish to meet its deadline in a schedule where all filled orders finish by time t.

$$P(i,t) = \begin{cases} 0, & \text{if } i = 0 \text{ or } t = 0 \\ P(i-1,t), & \text{if } i > 0, t > 0, \text{ and } t' < \ell_i \\ \max(P(i-1,t), P(i-1,t'-\ell_i) + p_i), & \text{otherwise} \end{cases}$$
 (†)

<u>Justification why (†) is a correct formula to compute (*):</u> For the base case, if there are no orders (i = 0) or there is no time to complete any order (t = 0), the maximum possible profit is obviously 0. Therefore, P(i,t) = 0 in this case, as wanted

For i > 0 and j > 0, if $t' < t_i$, there is no way to schedule order i so that it finishes by its deadline and by t. So, the maximum profit to schedule orders 1..i up to time t is the same as the maximum profit to schedule orders 1..i - 1 up to time t. Therefore, P(i,t) = P(i-1,t) in this case, as wanted.

Finally, if i > 0, j > 0, and $t' \ge \ell_i$, there are two possibilities.

- The optimal schedule S for orders 1..i up to time t does **not** include order i. In this case S is also an optimal schedule for orders 1..i 1 up to time t, so P(i,t) = P(i-1,t).
- The optimal schedule S for orders 1..i up to time t includes order i. Since $\ell_i \leq t' \leq d_i$, order i can be scheduled in the interval $(t' \ell_i, t')$. Furthermore, all other orders that are scheduled in S can be scheduled before time $t' \ell$: This is because, if in fact order i is scheduled at an earlier interval in S, we can move it to the interval $(t' \ell_i, t')$, this creating room to move all orders that were originally scheduled after order i to earlier non-overlapping intervals, so that they still meet their deadlines. So, without loss of generality, we can assume that in S orders 1..i-1 are scheduled before time $t' \ell_i$ and order i is scheduled in the interval $(t' \ell_i, t')$. Let S' be the schedule that schedules orders 1..i-1 as S but it does not schedule order i—i.e., $S'(i) = \infty$. So, the total profit of S is the total profit of S' plus the profit of order i. By a cut-and-paste argument S' is an optimal schedule for orders 1..i-1 up to time $t' \ell_i$. So, in this case, $P(i,t) = P(i-1,t'-\ell_i) + p_i$.

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From the above two cases, we conclude that, if i > 0, j > 0, and $t' \ge \ell_i$, $P(i,t) = \max(P(i-1,t), P(i-1,t'-\ell_i) + p_i)$, as wanted.

Solving the original problem: By the definition of the subproblems (*), the required return value is $P(n, d_n)$.

Pseudocode:

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\begin{aligned} & \text{MAXPROFIT}(\{(d_i, \ell_i, p_i): \ 1 \leq i \leq n\}) \\ & \text{1} & \text{sort the orders by non-decreasing deadline} \\ & \text{2} & \textbf{for } t := 0 \textbf{ to } d_n \textbf{ do } P(0, t) := 0 \\ & \text{3} & \textbf{for } i := 1 \textbf{ to } n \textbf{ do } P(i, 0) := 0 \\ & \text{4} & \textbf{for } i := 1 \textbf{ to } n \textbf{ do} \\ & \text{for } t := 0 \textbf{ to } d_n \textbf{ do} \\ & \text{5} & t' = \min(t, d_i) \\ & \text{6} & \textbf{if } t' < \ell_i \textbf{ then } P(i, t) := P(i - 1, t) \\ & \text{7} & \textbf{else } P(i, t) := \max \left(P(i - 1, t), P(i - 1, t' - \ell_i) + p_i\right) \\ & \text{8} & \textbf{return } P(n, d_n) \end{aligned}
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<u>Running time</u>: The running time of the algorithm is $\Theta(nd_n)$. This is pseudopolynomial, because it is polynomial in the input **value**, but not in the input **size**. In particular, d_n is exponentially larger than the size of its representation.

This problem is actually NP-hard, so it is unlikely that it has a truly polynomial-time algorithm.

c. The idea is to "step" through P(-,-) backwards starting at $P(n,d_n)$, and use the value of P(i,t) to determine whether order i is included in the optimal schedule (this is the case if $P(i,t) \neq P(i-1,t)$, which means that $P(i,t) = P(i-1,\min(t,d_i) - \ell_i) + p_i$), and if so we schedule it to finish at time $\min(t,d_i)$. In the above pseudocode we replace line 8 by the following:

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\begin{array}{ll} 1 & i:=n; \ t:=d_n \\ 2 & \textbf{while} \ i\neq 0 \ \textbf{do} \\ 3 & \textbf{if} \ P(i,t)=P(i-1,t) \ \textbf{then} \ S(i):=\infty; \ i:=i-1 \\ 4 & \textbf{else} \ S(i):=\min(t,d_i); \ i:=i-1; \ t:=\min(t,d_i)-\ell_i \\ 5 & \textbf{return} \ S \end{array}
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Answer to Question 2. Let B[1..n,1..n] be the given $n \times n$ array of 0s and 1s. For a square-of-ones (i,j,ℓ) in B, define its lower-right corner (LRC) to be $(i+\ell,j+\ell)$ and its size to be ℓ .

<u>Definition of the subproblems that our dynamic programming algorithm will solve:</u> For $1 \le i, j \le n$

S(i,j) = the maximum size of a square-of-ones among all squares-of-ones whose LRC is (i,j) (*)

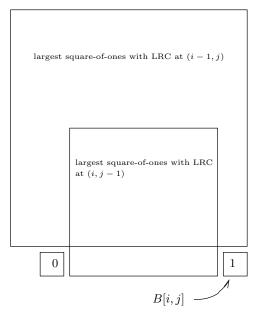
Recursive formula to compute each subproblem:

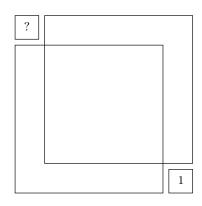
$$S(i,j) = \begin{cases} B[i,j], & \text{if } i = 1 \text{ or } j = 1\\ 0, & \text{if } i > 1, \ j > 1, \text{ and } B[i,j] = 0\\ m + B[i - m, j - m], & \text{if } i > 1, \ j > 1, \text{ and } B[i,j] = 1,\\ & \text{where } m = \min(S(i - 1, j), S(i, j - 1)) \end{cases}$$
 (†)

Justification why (†) is a correct formula to compute (*): The first two cases (i.e., when i = 1 or j = 1, and when B[i,j] = 0 are immediate from the definition of S(i,j).

The third case requires explanation, and the figure below may help clarify the discussion. First, by a cut-and-paste argument, $S(i,j) \le m+1$: otherwise the entire $(m+2) \times (m+2)$ square whose LRC is (i,j) would consist entirely of 1s; therefore, the two $(m+1) \times (m+1)$ squares whose LRCs are (i-1,j) and (i,j-1) would both consist entirely of 1s. Thus, $\min(S(i-1,j),S(i,j-1)) \ge m+1$, contradicting the definition of m.

Next, we show that $S(i,j) \ge m$. The $(m+1) \times (m+1)$ square with LRC (i,j) consists entirely of 1s, with the possible exception of B[i-m,j-m]. This is because, by definition of m, the two $m \times m$ squares with LRCs (i-1,j) and (i,j-1) consist entirely of 1s. Together with the bit B[i,j] which is 1 (by the hypothesis of the case), this covers the entire $(m+1) \times (m+1)$ square with LRC (i,j), with the exception of B[i-m,j-m]. So, in this case, if B[i-m,j-m]=1 then S(i,j)=m+1; otherwise, S(i,j)=m. In other words, S(i,j)=m+B[i-m,j-m], as wanted.





Largest square-of-ones with LRC above and to the left of (i, j) have different sizes

Largest square-of-ones with LRC above and to the left of (i, j) have the same size

<u>Solving the original problem:</u> By the definition of the subproblems (*), the required return value is the triple (i, j, S(i, j)) such that S(i, j) is maximum.

Pseudocode:

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\begin{array}{l} \text{for } i := 1 \text{ to } n \text{ do } S(i,1) := B[i,1] \\ \text{for } j := 1 \text{ to } n \text{ do } S(1,j) := B[1,j] \\ \text{for } i := 2 \text{ to } n \text{ do} \\ \text{ for } j := 2 \text{ to } n \text{ do} \\ \text{ if } B[i,j] = 0 \text{ then } \\ S(i,j) := 0 \\ \text{ else } \\ m := \min \bigl( S(i-1,j), S(i,j-1) \bigr) \\ S(i,j) := m + B[i-m,j-m] \\ \ell^* := 0 \\ \text{for } i := 1 \text{ to } n \text{ do} \\ \text{ for } j := 1 \text{ to } n \text{ do} \\ \text{ if } S(i,j) > \ell^* \text{ then } i^* := i; \, j^* := j; \, \ell^* := S(i,j) \text{ then } \\ \text{if } \ell^* = 0 \text{ then return } (0,0,-1) \\ \text{ else return } \bigl(i^* - (\ell^*-1),j^* - (\ell^*-1),\ell^*-1 \bigr) \end{array}
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<u>Running time</u>: The running time of this algorithm is obviously $\Theta(n^2)$.

Answer to Question 3.

- (1) Run the Floyd-Warshall algorithm on the given graph G to find shortest paths between every pair of nodes. Let D(u, v) be the weight of a shortest $u \to v$ path as computed by this algorithm $(D(u, v) = \infty)$ if there is no such path), and P(u, v) be the predecessor of v on a shortest $u \to v$ path (NIL if u = v).
- (2) Construct a weighted graph G' = (V', E') such that $(u, v) \in E'$ if and only if $D(u, v) \leq d$, with edge weight function $\mathbf{wt}' : E' \to \mathbb{R}$, where $\mathbf{wt}'(u, v) = D(u, v)$. This represents a map of only the towns with gas stations and and edge between two towns only if you can drive from one to the other in your car without refuelling.
- (3) Run Dijkstra's algorithm on G' with start node s and edge weights \mathbf{wt}' to find, for every node $u \in V'$, the weight D'(u) of a shortest $s \to u$ path in G', and the predecessor P'(u) of u on a shortest $s \to u$ path in G'. (Note that $s, t \in V'$, so s and t are nodes in G'.)
- (4) If $D'(t) = \infty$ then there is no route you can follow to drive from s to t in your car. Otherwise, use P' and P to recover the desired path: First let $u_1 = s, u_2, \ldots, u_k = t$ be a shortest $s \to t$ path in G': this is the reverse of the path $t, P'(t), P'(P'(t)), \ldots, s$. Then use P to find the shortest $u_i \to u_{i+1}$ path p_i in G, for each $1 \le i \le k-1$: this is the reverse of the path $u_{i+1}, P(u_i, u_{i+1}), P(u_i, P(u_i, u_{i+1})), \ldots, u_i$. Finally, concatenate $p_1, p_2, \ldots, p_{k-1}$ and return the resulting path.

Let n be the number of nodes and m be the number of edges in the given graph G.

- The Floyd-Warshall algorithm (step (1)) takes $O(n^3)$ time.
- Constructing the graph G' (step (2)) takes $O(n^2)$ time. (Note that G' has O(n) nodes and $O(n^2)$ edges.)
- Dijkstra's algorithm (step (3)) takes $O(n^2 \log n)$ time.
- Recovering the path (step (4)) takes O(n) time.

Thus, the overall running time is $O(n^3) + O(n^2) + O(n^2 \log n) + O(n) = O(n^3)$ time.