# CMPSC 623 Problem Set 6. by Prof. Honggang Zhang

Out: November 6, 2007 Due: November 13, 2007, before class.

### **Problem 1** Page 378, 16.1-2.

This proof is very similar to the proof for Theorem 16.1 in textbook.

Consider  $S_{ij} = \{a_k \in S : f_i \le s_k < f_k \le s_j\}.$ 

Let  $a_m$  be the activity in  $S_{ij}$  with the latest start time, that is,  $f_m = max\{s_k : a_k \in S_{ij}\}$ . We first observe that  $S_{mj}$  is empty, as there is no other activity in  $S_{ij}$  that has a later start time than that of  $a_m$ .

We further observe that  $a_m$  is used in some max-size subset of mutually compatible activities in  $S_{ij}$ . In order to show this, first lets assume that we have  $A_{ij}$ , a max-size subset of mutually compatible activities of  $S_{ij}$  and lets order the activities in  $A_{ij}$  in monotonically increasing order of starting time. Let  $a_k$  be the last activity in  $A_{ij}$ . If  $a_k = a_m$ , we are done. Otherwise, construct a new subset  $A'_{ij} = A_{ij} - \{a_k\} \cup \{a_m\}$ . Clearly  $A'_{ij}$  is also a max-size solution for  $S_{ij}$  as all activities in  $A'_{ij}$  are mutually compatible and its size is the same as that of  $A_{ij}$ .

Based on these two observations, we see that to look for a max-size set solution for  $S_{ij}$ , we can simply choose the latest starting-time activity in  $S_{ij}$ , and then recursively solve a smaller subsubproblem  $S_{im}$ . This will give us a sequence of greedy choices when solving for  $S_{0(n+1)}$ . This sequence of greedy choices is an optimal solution for the original problem.

#### **Problem 2** Page 384, 16.2-1.

Define a subproblem  $S_{ij}$  as the set of items from 1 to i and the knapsack has capacity j. Define  $A_{ij}$  as the optimal set of fractional items for subproblem  $S_{ij}$  and let  $F_{ij} = \{k \in A_{ij} : 0 < f_k \le 1\}$  be the set of corresponding optimal fractions. That is, a complete optimal solution is given by  $S_{ij}$  and  $A_{ij}$ . Let the corresponding optimal value be knap(i,j).  $A_{ij}$  contains an optimal collection of items. An item k in  $A_{ij}$  has a certain fraction of its weight  $f_k w_k$  used in computing the optimal value knap(i,j). That is,  $knap(i,j) = \sum_{k \in A_{ij}} v_k f_k$ .

We would like to show this problem has the greedy-choice property, that is, a globally optimal solution can be arrived by making a locally optimal greedy choice. Specifically for this problem, we would like to show that the most valuable item in subproblem  $S_{ij}$  must be in some optimal set. Let item m be the most valuable item in  $S_{ij}$ , that is,  $v_m = max\{v_k : 1 \le k \le i\}$ . We sort all items in  $A_{ij}$  in terms of decreasing value, and pick the most valuable item k. We can always replace item k's weight  $f_k w_k$  in the optimal knapsack with the same weight  $f_m w_m$  (where  $f_m = f_k w_k / w_m$ ) if  $w_m \ge w_k$ , or with weight  $w_m$  of item m plus weight  $f_k w_k - w_m$  of item k if  $w_m < w_k$ . Then this new optimal solution for  $S_{ij}$  has a total value no less than that of optimal solution given by  $A_{ij}$  and  $F_{ij}$ . This shows the greedy-choice property, that is, we can always choose the current most valuable item and put it into the knapsack as much as we can, and then fill the rest of the knapsack by solving a smaller subproblem following a similar greedy stategy.

## **Problem 3** Page 384, 16.2-3.

Lets sort items in increasing weight  $w_1 \leq w_2 \leq ... \leq w_n$ , then as stated in the problem description, we have  $v_1 \geq v_2 \geq ... \geq v_n$ .

We can simply design a greedy algorithm in which we scan all items starting from item 1. Whenever we check item i, we put it into the knapsack if it can fit into the current remaining capacity of the knapsack, that is if  $w_i \leq W - \sum_{k \in A_{i-1}} w_k$  where  $A_{i-1}$  is the optimal set of items when considering items from 1 to i-1.

This problem clearly has greedy choice property. Consider subproblem  $S_{ij}$  where we consider items from 1 to i and knapsack capacity is j. Let m be the most valuable item in  $S_{ij}$ . We can show that m must be in some optimal solution for  $S_{ij}$ . Let  $A_{ij}$  be one optimal set for subproblem  $S_{ij}$ . Let k be the most valuable item in  $A_{ij}$ . If k=m, then we are done. Otherwise, we can replace k with m to get  $A'_{ij} = A_{ij} - \{k\} \cup \{m\}$ . The total weight of items in  $A'_{ij}$  is no larger than that of  $A_{ij}$  (because  $w_m \leq w_k$ ), but its value is no less than that of  $A_{ij}$ , so  $A'_{ij}$  must be an optimal solution. Thus, we have proved the greedy choice property.

## **Problem 4** Page 384, 16.2-4.

Suppose that there are m gas stations in total. Lets call the gas station closest to the starting point  $g_1$ , and label all other gas stations as  $g_2, g_3, ...g_m$  where a larger index of a gas station indicates that the gas station is further away from the starting point. Let  $d_i$  denote the distance between  $g_i$  and  $g_{i-1}$ .  $d_1$  denotes the distance between  $g_1$  and the starting point.  $d_{m+1}$  denotes the distance between the destination and  $g_m$ .  $d_0$  denotes the distance between the starting point and itself, so it equals 0.

We can design a simple greedy algorithm to solve this problem. The idea is like this:

```
i=0
while i < m
   d < - 0
   k <- i
   while d <= n AND k <= m
                              //stop if the total miles exceed n
       k < - k+1
       d \leftarrow d+d[k]
   end
   if d > n
       print "stop at gas station k-1"
       i < - k-1
                             //we start again at gas station k-1
       continue
   else if k > m
       exit while loop
end
```

This algorithm is greedy in the sense that we always drive as far as we can (if within n miles). This problem has greedy choice property. To see this, let  $g_p$  be the first furthest gas station we can reach using one full tank of gas. That is, p is the largest index i to maximize

 $\{d_1+d_2+...+d_i\}$  subject to constraint  $d_1+d_2+...+d_i\leq n$ . We can show that p must be in one optimal solution. Let  $A_{1m}$  denote the optimal set of gas stations for the original problem and let k be the largest index gas station in in  $A_{1m}$ . If k=p, we are done. Otherwise, let  $A'_{1m}=A_{1m}-\{k\}\cup\{p\}$ . Clearly,  $g_k$  cannot be further away from starting point than  $g_p$  and we can drive from starting point to  $g_p$  without gas re-filling (based on the definition of  $g_p$ ), so  $A'_{1m}$  is also a valid solution. Also because  $|A'_{1m}|=|A_{1m}|$ , so we know  $A'_{1m}$  is also an optimal solution. After we first choose a locally best gas station p, then we can follow a similar argument to show we can always choose the current best gas station for the remaining sequence of subproblems. This completes our proof.