

Analysis of Algorithms Homework 2

Question 1.

```
dynamicKnapsackSol(int n, int W, int weight[], int value[]){
    Let K be table of [n+1][W+1]
    for(i = 1; i < n; i++)
        K[i][0] = 0
    for(j = 1; j < W; j++)
        K[0][j] = 0

    for(i = 1; i < n; i++)
        for(j = 1; j < W; j++)
            if(j < i*weight[i])
                K[i][j] = K[i-1][j]
            else
                K[i][j] =
                    max(K[i-1][j], K[i-1][j-weight[i]]+value[i])
    //K[n][W] is the final answer
}
```

The algorithm takes as inputs the maximum weight W , the number of items n and two sequences $v = \{v_1, v_2, \dots, v_n\}$ and $w = \{w_1, w_2, \dots, w_n\}$. The $c[i][j]$ values are stored inside a table $c[0 \dots n][0 \dots W]$ whose entries are computed in the following order. The first row of C is filled from left to right then second third and so fourth. At the end of the algorithm, $c[n][W]$ contains the maximum value the thief can take

Question 2.

A greedy algorithm would solve this problem optimally. If we maximize the distance that can be covered from some particular point, there is a place to get gas if we run out. Our first stop should be at the longest point from the initial starting position, which would be \leq to m miles away. The problem at hand also exhibits optimal substructure because once we have chosen our first stopping point p , we solve the sub-problem with the assumption we are starting at p . Adding these two plans together yields an optimal solution. It's important to show that the greedy approach yields a first stopping point contained in some optimal solution. Let R be an optimal solution with the professor stopping at positions r_1, r_2, \dots, r_k . Let f_1 denote the farthest stopping we can reach from the starting point. Then we can replace r_1 by f_1 to create a generate a modified solution F since $r_2 - r_1 < r_2 - f_1$. In essence, we can make it to the positions contained in G without running out of gas. Since G has the same amount of stops, we can safely conclude that f_1 is contained inside some optimal solution. Therefore a greedy approach is valid.

Question 3.

Part A

Where T is initial tour

Generate permutation generates another possible combination of cities

Score calculates the total tour cost

```
bruteForceSolver(T) {  
    best_tour = T  
    best_score = score(T)  
    while(permutations of T)  
        S = score(T)  
        generatePermutation()  
        if(s < best_score)  
            Best_score = s  
            Best_tour = tour  
}
```

Run time is $(n-1)!$ Which is incredibly slow

Part B

Observation: Consider any shortest path in our TSP graph G . Then any subpath of this shortest path is also a shortest path (between its own endpoints). So, the above observation suggests that TSP exhibits the optimal substructure that will allow us to use DP

```
FindMinRoute(Tsp[][]){
    let sum = 0
    let increment = 0
    let j = 0
    let i = 0
    let minVal = infinity
    let visitedRouteList be a empty list
    visitedRouteList.add(0)
    Let route be table of [tsp.size()]

    while (i < tsp.size and j < tsp[i].size) {
        /* This is the corner of the 2x2 array*/
        if (increment >= tsp[i].size - 1) {
            break
        }
        /* If this path has not been visited then
        and if cost is less then, update the cost */
        if (j != i and !(visitedRouteList.contains(j))) {
            if (tsp[i][j] < minVal) {
                minVal = tsp[i][j]
                route[increment] = j + 1
            }
        }
        j++

        /* Check all paths from the
        ith city */
        if (j == tsp[i].size) {
            sum += minVal
            minVal = infinity
            visitedRouteList.add(route[increment] - 1)
            j = 0
            i = route[increment] - 1
        }
    }
}
```

```

        increment++
    }
}
/* Update the ending city in array
   from city which was last visited */
i = route[increment - 1] - 1
for (j = 0; j < tsp.size; j++) {
    if ((j != i) and tsp[i][j] < minVal) {
        minVal = tsp[i][j]
        route[increment] = j + 1
    }
}
sum += minVal

```

Run Time: $O(N^2 \log_2 N)$

Assume $n = 4$

Assume we have a graph whose edges cost as follows

$c(AB) = 100$

$c(AC) = 101$ $c(BC) = 100$

$c(AD) = 200$ $c(BD) = 101$ $c(CD) = 150$

If the algorithm starts from A it will generate a tour of ABCDA with a cost of $100+100+150+200$ which is 550 which is a very inefficient solution

Part C.

/ Recursive Solution*/*

```
def TSPGetMinDistance(mainSource, source, cities)
    if len(cities) == 1
        minDis = GetCostVal(source, cities[0], mainSource) +
GetCostVal(cities[0], 0, mainSource)
        return minDis
    else
        Dist = [] is a list
        for city in cities
            cities = cities[city]
            dcities.remove(city)
            Dist.add(GetCostVal(source, city, source) +
TSPGetMinDistance(mainSource, city, dcities))
        iterative_process.add(Dist)
        return min(Dist)
```

Worst Case Run Time: $O(2^n n^2)$

Space complexity: $O(2^n n)$.

This is our cost matrix. The diagonals are 0 because the distance from a city to itself is just 0.

$$E = \begin{bmatrix} 0 & 10 & 15 & 20 \\ 5 & 0 & 9 & 10 \\ 6 & 13 & 0 & 12 \\ 8 & 8 & 9 & 0 \end{bmatrix}$$

$$g(2, \emptyset) = c_{21} = 5$$

$$g(3, \emptyset) = c_{31} = 6$$

$$g(4, \emptyset) = c_{41} = 8$$

$$F = g(1, \{2, 3, 4\}) = \min(\{c_{12} + c_{23} + c_{34} + c_{41}\} , \\ \{c_{13} + c_{32} + c_{24} + c_{41}\} , \{c_{14} + c_{42} + c_{23} + c_{31}\})$$

$$= \min (\{10+9+12+8\} , \{15+13+10+8\} , \{8+8+9+6\})$$

$$= \min (\{39\}, \{46\}, \{31\})$$

= 31 is the shortest distance

City (1->2, 2->3, 3->4)

$$10+9+12 = 31$$

/* Garbage Attempt*/

A set of locations V and a cost function c that calculates distance

Assume D_{tsp} is infinity

DynamicTSP(N, s)

 Visited[s] = 1

 Cost = 0

 if ($N = 2$ and $k \neq s$)

 Cost(N, k) = dist(s, k)

 Return cost

 Else

 for($j = 0; j < N; j++$)

 for($i = 0; i < N$ and visited[i] = 0; $i++$)

 if($i \neq s$ and $j \neq s$)

 Cost(N, j) =

/*Garbage Attempt code did not work */