# Question 1

1. **Least Total Cost Recurrence**

The goal here is to write down a recurrence for , where represents the least total cost of going from the source square to square in the grid. Since this problem possesses optimal substructure, then this means that an optimal solution to a problem contains within it optimal solutions to subproblems. In this case, for the least total cost to get from the source square to any square , there exists within the grid the least total costs to get from the source square to any other square not , so long as it is reachable from the source square and is not an illegal move. This implies that the least total costs are dependent on other least total costs, a property it possesses via optimal substructure.

For any square , let represent the square immediately before , where its least total cost is dependent on it. Then, let represent the cost to get from square to square as stored in the cost function . Thus, the following recurrence can be written for as follows:

For the third case, this recurrence says that: for any square that does not fall under the first two cases, take the minimum between either what is already there as the least total cost for square , or take the least total cost for square plus the cost to get from square to square . For part (c) of this question, this conditional logic is coded in the Python program as follows:

This says that if the stored least total cost in square is greater than the stored least total cost in square plus the cost to get from to , then update the least total cost of square . This logic is needed because for a square , assuming it is not on the edge of the grid, there are at most ways for its least total cost to be updated: , , , or no update. This recurrence stores the least of these, assuming validity, as and performs the stated comparison.

1. **Least Cost Path Recurrence**

The goal here is to write down a recurrence for , where represents the least cost path to get from the source square to some square . Similar to what was mentioned in part (a), the optimal or least cost path can be “lopped off” or “eaten into” from the right side of the problem, i.e., starting from the destination and going backwards towards the source. First, going in the forward direction of the algorithm, the final least total cost will be obtained once it processes all the set of moves in the cost function . The total cost in the set of destination squares with the lowest value is the last value in the optimal path, since the algorithm seeks the least cost path.

From here, the recurrence can be realized by working backwards, meaning from an optimal destination square , determine all the immediately previous squares that it could have come from. If at the left edge of the grid , it would have either come from or . Similarly, if at the right edge of the grid , it would have either come from or . Lastly, if anywhere in between (not including source squares), it would have come from either , , or .

The algorithm determines which one it comes from by choosing the preceding square with the least total cost from the source up to that point, hence it is dependent on the function from part (a). However, for the algorithm this is already known, as the program in part (c) tracks not only the optimal squares to take, but also the parent of those optimal squares, or in other words, where they came from when building the dynamic programming array. This strategy can be extended for every square in the optimal path, in a backwards manner, until the source square is reached. With that being said, the following recurrence can be written for as follows:

In words, for some square , the algorithm chooses the least cost square from one of , , and , and appends that to its least cost path. This decision is based on each of their costs from part (a). If represents the least cost immediately previous square, then this is taken because is the least total cost.

# Question 2

1. **Optimal Substructure**

Optimal substructure is the property that an optimal solution to a problem contains within it optimal solutions to subproblems. We are given as input a set of stops , where each is reachable from if started at the beginning of the day, and in terms of distance from the source A. For single-source minimal stops: if is a minimal stop path from to , then the sub-path is a minimal stop path from to . Suppose is an optimal sequence of stops that get us from A to B such that the distance from source A is maximized for each stop. A sub-problem for which has to be an optimal solution: suppose in the input, the stops are ordered by increasing distance from A. Then: has to be an optimal solution to all stops that end at or before . In other words, if B is stop , the optimal solution is some . Then, if B becomes stop , then the optimal solution becomes . Thus, no matter what stop B is at, the optimal solution stays the same up to that stop B. This is the optimal substructure that this problem possesses.

1. **Feasibility**

The goal is to prove that an instance of the problem is feasible if and only if for every consecutive pair in the input, we can drive from to within a day.

Proof by contradiction: suppose the drive cannot be made. Since the drive could not be made, then we must have stopped at and never have been able to make it to . Let be the maximum distance we can drive within a day. Since we could not make it to stop , then , i.e., the distance between the stops is greater than what we can possibly drive. Since the input claims there is some path from to , i.e., is feasible, then there must exist some sub-path in that path that starts before and ends at or after . Since the drive could not have been made from , then it must have been made from some stop where . But then we have , so this path from to is also not possible. We have reached our desired contradiction, in that the assumption that the drive cannot be made is wrong, therefore for every consecutive pair in the input, we can in fact drive from to within a day.

1. **Fewest Stops Recurrence**

The goal is to write a recurrence for , where is the fewest stops we have to make to get from to . Let be the stop number, which will allow our recurrence to represent the stops we must make. For every stop, we can choose to either keep going if we can make it to the next stop before nighttime or stop if we cannot make it. In this case, we want to choose the option which minimizes our number of stops. Therefore, the recurrence is:

In words: if we have reached stop from stop , we do not need any more stops so return . If we can get from stop to stop (), then simply proceed to the next stop without counting a stop. Conversely, if we cannot get from stop to stop (), then add to the stop count and proceed to the next stop. Lastly, if the input is infeasible, return mnemonic .

1. **Pseudocode**

const int NumMinStops(const vector<int> stops) {

const int numStops = stops.size();

vector<int> m(numStops + 1, 0);

for (int j = 0; j < numStops; j++) {

for (int i = j; i >= 0; i--) {

if (stops[i] stops[j]) {

m[j + 1] = m[j];

} else if (stops[i] stops[j]) {

m[j + 1] = 1 + m[j];

}

}

}

if (m.back() != 0) {

return m.back();

}

return ;

}

The algorithm was written out fully in C++ to be able to test with different inputs for the set of stops, namely, . Afterwards, the following notations were used: to represent being able to get from to , to represent not being able to get from and , and to represent there being no feasible sequence.

The function starts out by initializing the dynamic programming array ( in this case), of the size of the number of stops, all set to a value of . Then, the algorithm loops through each stop and does the following: for each stop up to stop , update the dynamic programming array. If the stop can be made (), then make no changes to the count in that part of the array (). Conversely, if the stop cannot be made (), then add to its stop count before proceeding to the next one (). Lastly, if stop has been reached (), then that value is automatically since it was initialized to in the first place. Finally, the last element in the array is the answer: if it has been updated then return that result, else return the mnemonic , as this means that no path from to has been found.

Let be the number of acceptable stops in the input . The worst-case time efficiency of this algorithm is . First, we must iterate through each of the stops once, which results in a time complexity of exactly . Then, for each of the stops, the algorithm must loop from to to update the dynamic programming array to track the number of stops. This operation also results in a time complexity of exactly . Thus, in the worst-case, the algorithm loops through stops, and for each of them, loops number of times to update the array. Therefore, the time efficiency of this algorithm is .

The space efficiency of this algorithm is . The data structure used to store the minimum number of stops is a vector (array) of size , where is the size of the input . And since is the number of acceptable stops in the input , then . Also note that the constant can be omitted from the space efficiency. Therefore, the space efficiency of this algorithm is .

# Question 3

1. **Lower and Upper Bounds on Alignment Length**

The goal here is to determine the lower- and upper-bounds on the alignment length of the edit distance problem. To help answer this question, code was written in C++ using dynamic programming to test with different inputs to see the results. The following snippet of the code contains the most important part of the program, which is the build-up of the dynamic programming array as follows:

for (int i = 1; i <= n; i++) {

dp[i][0] = i;

}

for (int j = 1; j <= m; j++) {

dp[0][j] = j;

}

for (int i = 1; i <= n; i++) {

for (int j = 1; j <= m; j++) {

if (x[i-1] == y[j-1]) {

dp[i][j] = dp[i-1][j-1];

} else {

dp[i][j] = min(dp[i-1][j-1],

min(dp[i-1][j], dp[i][j-1])) + 1;

}

}

}

Just like from Lecture 7c, using and , we get an alignment length of with this algorithm. Furthermore, this algorithm follows exactly the recurrence realized for edit distance from the lecture:

This algorithm follows a bottom-up approach, where it fills in a table , starting at and ending at , and then returns as the answer. The algorithm contains four loops: the first two correspond to the first two cases in the recurrence above. For the nested loop, it iterates times, and for each letter: if they are equal, i.e., , then leave the character unchanged for a cost of . If they are not equal, then take the minimum between substitution (), deletion (), and insertion (), all for a cost of .

Now, analyzing time efficiency, the costliest operation in the algorithm is the nested for loop that iterates times in order to update the dynamic programming array. Thus, this has a time efficiency of . In addition, the first two loops run in times and , respectively. And assuming the worst-case scenario, which corresponds to deleting every character in and inserting every character in , the total upper bound time efficiency is . Since the nested loop must iterate through the entirety of the dynamic programming array to analyze the strings, then this also results in a lower bound time efficiency of . For lower bound, since all characters from string must appear in sequence in the top row, and similarly for string in the bottom row, then it makes sense that the algorithm would still have to iterate through the entire array to analyze the whole string. Therefore, this also results in a tight bound of for the edit distance problem.

1. **Worst-Case Number of Possible Alignments**

* May end up with something more than . The problem asks only that you establish as a lower bound, as that is what means.