

CSE 321 HW5 171044052

Q1) Firstly, I split all my elements into smaller sub arrays. Then I compare two words until the end of the shortest one. If my arrays have a common letter, I store this letter in an array. Lastly, I found a common word. Based on the merge sort technique. Then I merged all letters and created a string.

Worst case of this code, $O(n \log(n))$. Splitting array into subarrays takes $\log(n)$ time, and comparing words letter by letter takes $O(n)$. These are nested so, it takes $O(n \log(n))$.

Q2)a) In this question, I split my arrays until I get 2 or 1 element left. And look for right side elements of arrays, and left side elements of arrays. I solve like this because I can not sell before buying the product. Then in the inner function, I found my bigger element in the right prices subarray. Then I extracted all of the left prices subarray elements from it. I found profit and everytime I found a bigger profit, I updated max Income. I tried the return positions of buy time and sell time but I could not be successful. My idea was getting buy value and sell value from subarrays and search their indexes in my biggest array. But I could not use tuple values.

Worst case of this code, $O(n \log(n))$. Splitting array into subarrays takes $\log(n)$ time, and every profit for subarrays takes $O(n)$. These are nested so, it takes $O(n \log(n))$.

b) In this part, I solved it with 2 nested loops. Inner loop, I compared all incomes of $arr[i]$ elements and $arr[j]$ elements. Then I stored their indices for printing. Then I returned a list which contains all of requested informations. This algorithm takes $O(n^2)$ time complexity for two nested loops.

c) First algorithm is faster than second algorithm in worst case scenario.

Q3) In this question, Firstly I filled `lengthOfArray` with 1's until length of input array. Then in nested for loops, I think them as subarrays. If my i is 4, this means that I have a sub array with 4 element. And I looked how many element in this sub array is smaller than my $arr[i]$ element. If this element is smaller than $arr[i]$ and all elements of $arr[j]$ is smaller $arr[j+1]$, then this is an increasing sub array. I increased my store array inputs for every increasing sub list, for example, if my i is 4 and subarray is 1,2,3,4 then I increase my `storeSubArrayCounts[i]` for every consecutive element. So my `storeSubArrayCounts[i] = 4` and that means my 4th sub array has 4 element consecutive.

Worst case is equal to $O(n^2)$ because I have two nested loops.

Q4)a) Firstly I created `storeScores` array for storing my score result and paths. Then I assign my first score (`score[0][0]`) in this list. Because players always must to start at this point. At each element in the array, the algorithm compares the highest-scoring

path that ends at the element above it with the highest-scoring path that ends at the element to its left. Then it chooses the path with the higher score and adds the current element to that path. The resulting path and its score are stored in the storeScores list.

b)In greedy approach, every move must be played as biggest side. There is no control for biggest path. Look for only next move and next move must be biggest one in choices. So I go for biggest score for every path.

c)For correctness, brute force and dynamic approach can solve this game correct for every situation because they found every path. But in greedy, it goes biggest score for every move. It does not control every path. So in greedy, there can be false results.

For time complexity. Brute force solve this problem in two nested loops. Which has $O(n^2)$ time complexity. In my dynamic programming approach, I too solve this problem in $O(n^2)$ for worst case. But in greedy, the complexity is equal to $O(\text{row} + \text{column})$. And it's linear. So greedy is faster than these two algorithms.