

Question #7

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function findMaxDiscount(stores, currentSet):
    if store is empty:
        return calcDiscount(currentSet)

```

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    maxDiscount = 0

```

```

    bestSet = None

```

```

    for each store in stores:

```

```

        newSet = current + {store}

```

```

        remainingStore = stores - store

```

```

        discount = findMaxDiscount(remainingStore, newSet)

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    if (discount > maxDiscount):

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        maxDiscount = discount

```

```

        bestSet = newSet

```

```

    return bestSet

```

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initialStores = [list of all stores]

```

```

maxDiscountSet = findMaxDiscount(initialStores, [])

```

Base case: When $n=0$ (no stores left) the function simply calculates and return the discount for the current set. we can consider this a constant time operation $O(1)$, so $T(0) = 1$

Recursive case: When there are n stores to consider the function iterates over each store removes it from the list and makes a recursive call with $n-1$ stores. For each recursive call it also performs some constant-time operations (like adding a store to current set calculating the discount and comparing discounts).

The recursive relation can be formulated as:

$$T(n) = n \cdot T(n-1) + O(1)$$

$$F(2) = 2 \cdot F(1)$$

$$F(1) = 1 \cdot F(0)$$

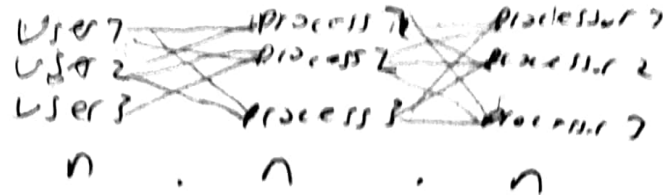
$$F(0) = 1$$

$$F(n) = n \cdot (n-1) \cdot (n-2) \cdot \dots \cdot 2 \cdot 1 \cdot F(0)$$

$$F(n) = n! \cdot F(0)$$

$$F(n) = \underline{\underline{n!}}$$

Question #2



Function FindMinCost (cost [Users[]], Process[], Processor[]):

For user each in Users

For processor each in Processors

For process each in Process

tmp-cost = CalculateTotalCost (user, process, processor)

if (tmp-cost < min-cost)

min-cost = tmp-cost

min-cost-user = user

min-cost-process = process

min-cost-processor = processor

return min-cost-user, min-cost-process, min-cost-processor

Timing Analysis:

Each for require n times. all for is time n^3

There aren't average, best, worst case. only timing analysis

$O(n^3)$

Question 43

9 8 7 ... 2 1 All Port Permutations

Function FindMinimumEnergySequence(parts):

min-energy = Infinity

min-sequence = []

for n times

for each sequence in allPermutations(parts): // return list of n! times

energy = calculateEnergy(sequence) // goes to paper

if energy < min-energy:

min-energy = energy

min-sequence = sequence

return min-sequence, min-energy

Function allPermutations(parts): // generate all possible permutations of the part using recursive approach
return list

Function calculateEnergy(sequence): // calculate the total energy cost for a given sequence

parts = [list of 7 parts]

optimal-sequence, energy-cost = FindMinimumEnergySequence(parts)

Worst-case complexity: The worst-case scenario occurs when the algorithm has to explore every possible sequence. Since we are generating all permutations of the parts the time complexity is $O(n \cdot n!)$

where n is number of parts. This is because there are $n!$ permutations for n parts

Best-case complexity: The best-case scenario would still require generating all permutations so the best-case complexity remains $O(n \cdot n!)$

Average-case complexity: On average the complexity would still revolve around the permutations of the parts, so it also stands at $O(n \cdot n!)$

function all-permutation (Ports)

if len(Ports) <= 7:
return (Ports)

else

all_sequences = []

for i in range(len(Ports)):

current_port = Ports[i] + Ports[i+7:]

for sequence in generate-all-possible-sequences(remaining-ports)

all_sequences.append([current_port] + sequence)

return all_sequences

```
Function minColn(cols,target):
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$$\min(\ln S(t_0, t^*)) = INF$$
$$\min(\sin[0]) = 0.$$

for i from 7 to 10, get i n

for j from 0 to size(words) - 1; A

17. $\cos(\pi/2) = 0$

$$\text{Sub Result} = \min(\text{colsum}[i] + \text{colsum}[j]) \quad 7(n-1)$$

17 subresult 1 = LNA and subresult 17 = min(abs(E1))

$$\min \text{Cost}(C) = 500000 / 1417$$

```
return min(cons[1:4])
```

$$T(n) = n^2 \cdot T(n-1)$$

7) Initialize an Array 'minCoins' to keep track of minimum number of coins required for each value up to the target amount. Set

$\text{min}(\text{coins})[\text{target}]$ to infinity and $\text{min}(\text{coins})[0]$ to 0 since zero coins are needed to make zero change

2) Using two nested loops iterate through the values from 1 to the target amount and iterate through each coin denomination.

3) For each value i' and each coin denomination j' , check if the coin denomination ($\text{coin}[j]$) is less than or equal to current value i' . If it is, calculate the subresult by accessing $(\text{min}(\text{coins}[i - \text{coin}[j]]))'$.

- if the sub-result is not infinity (meaning it's a valid value) and adding one coin to it would result in smaller number of coins than the current minimum for $\text{minCoins}[i]$ update $\text{minCoins}[i]$ to the new smaller value (subResult+1)

5) Finally return min (coins[i][j]) which contains the minimum number of coins need to make up exact target amount of change.

Time complexity: $O(n^2)$

7. The return loop from 7 to the forget value.

2. inner loop iterates through the available coin denominations.

The outer loop runs for up to the target value, so it executes 'target' times. Meanwhile, the inner loop operates based on the number of available coin denominations, which is represented by size (wins).

Always best + only worst case

$$T(n) = n^2 \cdot T(n-1)$$

Question #5

In function find-min-max we have two recursive call for each call to itself, each time with half of the array. This gives us the following recurrence relation.

$$T(n) = 2T\left(\frac{n}{2}\right) + f(n)$$

$T(n)$ is the time complexity of the function when called with an array of length n .

The term $2T\left(\frac{n}{2}\right)$ represent the time time complexity of the two recursive calls on half of the array.

$f(n)$ represent the time for all other operations within the function call, excluding the recursive calls.

Simplify Recursion Relation

$$T(n) = 2T\left(\frac{n}{2}\right) + c$$

$$T(n) = aT\left(\frac{n}{b}\right) + f(n)$$

$$a \geq b \quad b \geq 1$$

$f(n)$ asymptotically positive function

in our case $a=2$ $b=2$ $f(n)=c$ (c is $O(1)$)

$O(n^{\log_b a}) = O(n^0) = O(1)$ we fall in to case 2 of the master theorem where $f(n)$ is $O(n^{\log_b a})$

$$T(n) = O(n^{\log_b a}) = O(n^{\log_2 2}) = O(n)$$

$$T(n) = \begin{cases} c_1 & \text{if } n \leq 1, \\ 2T\left(\frac{n}{2}\right) + c_2 & \text{if } n > 1. \end{cases}$$