

### HW 3 ①

Can Duyar  
171044075

Q1)

a) Algorithm  $\text{alg1}(L[0 \dots n-1])$   
if  $(n == 1)$  return  $L[0]$   
else  
     $\text{tmp} = \text{alg1}(L[0 \dots n-2])$   
    if  $(\text{tmp} \leq L[n-1])$  return  $\text{tmp}$   
    else return  $L[n-1]$

→ This algorithm finds the smallest element of the given array.

$$T(n) = T(n-1) + 1 \text{ for } n > 1, T(1) = 0$$

$$T(n-1) = T(n-2) + 1$$

$$T(n-2) = T(n-3) + 1$$

$$T(n) = [T(n-2) + 1] + 1$$

$$T(n) = T(n-2) + 2$$

$$T(n) = [T(n-3) + 1] + 2$$

$$T(n) = T(n-3) + 3$$

∴ continue for  $K$  times

$$T(n) = T(n-K) + K$$

$$\hookrightarrow \text{Assume } n-K=1 \rightarrow K=n-1$$

$$T(n) = T(n-n+1) + n-1$$

$$T(n) = \underbrace{T(1)}_0 + n-1$$

$$\underline{T(n) = n-1}$$

Therefore,

$$\text{Time Complexity} \rightarrow \boxed{O(n)}$$

Result  
↑

b) Algorithm  $\text{alg2}(x[1 \dots r])$   
 if  $(l == r)$  return  $x[l]$   
 else  
      $\text{flr} = \text{floor}((l+r)/2)$   
      $\text{tmp1} = \text{alg2}(x[l \dots \text{flr}])$   
      $\text{tmp2} = \text{alg2}(x[\text{flr}+1 \dots r])$   
     if  $(\text{tmp1} < \text{tmp2})$  return  $\text{tmp1}$ ,  
     else return  $\text{tmp2}$

### Recurrence Relation

$$T(n) = T(\lceil n/2 \rceil) + T(\lfloor n/2 \rfloor) + 1 \quad \text{for } n > 1, T(1) = 0$$

$$T(n) = 2T(n/2) + 1$$

We can use backward substitution to solve it, with using  $n = 2^t$

$$\begin{aligned} T(2^t) &= 2T(2^{t-1}) + 1 = 2[2T(2^{t-2}) + 1] + 1 = 2^2T(2^{t-2}) + 2 + 1 \\ &= 2^2[2T(2^{t-3}) + 1] + 2 + 1 = 2^3T(2^{t-3}) + 2^2 + 2 + 1 = \dots \\ &= 2^pT(2^{t-p}) + 2^{p-1} + 2^{p-2} + \dots + 1 = \dots \quad \text{for } p = t \end{aligned}$$

$$\begin{aligned} &= 2^tT(2^{t-t}) + 2^{t-1} + 2^{t-2} + \dots + 1 = 2^t \cdot \overset{0}{T(1)} + 2^{t-1} + 2^{t-2} + \dots + 1 \\ &= 2^t - 1 = \underline{\underline{n-1}} \end{aligned}$$

$$\begin{aligned} T(2^t) &= 2^t - 1 & 2^t &= n \\ T(n) &= n - 1 \end{aligned}$$

Therefore Result  
Time Complexity =  $\mathcal{O}(n)$

$\Rightarrow$  As a result, time complexity is " $\mathcal{O}(n)$ " for both of the algorithms, so their performances are same. We can prefer both of them for the same problem! (But second algorithm calls itself 2 times and first algorithm calls itself 1 time, in this case maybe first algorithm can be better in terms of space)

(3)

Q2) Algorithm Polynomial-Brute-Force ( $P[0 \dots n], x$ )

```

t ← 0.0
for P ← n down to 0 do
  degree ← 1
  for g ← 1 to P do
    degree ← degree * x
  endfor
  t ← t + P[n-P] * degree
endfor
return t
end

```

Time complexity of the algorithm

$$T(n) = \sum_{P=0}^n \sum_{g=1}^P 1 = \sum_{P=0}^n P = 0 + 1 + \dots + n = \frac{n \cdot (n+1)}{2} = \frac{n^2 + n}{2}$$

Therefore,

Time complexity =  $\boxed{O(n^2)}$

⇒ It's possible to design an algorithm that has better complexity!

Algorithm Polynomial-Brute-Force2 ( $P[0 \dots n], x$ )

```

K ← P[n]
degree ← 1
for g ← 1 to n do
  degree ← degree * x
  K ← K + P[n-g] * degree } constant time for two operations
endfor
return K
end

```

Time complexity

$$T(n) = \sum_{P=1}^n 2 = 2n$$

we can ignore the coefficients

Therefore,

Time complexity =  $\boxed{O(n)}$



4

Q3)

Algorithm count\_substr\_brute\_force(str[0...n-1], start, end)

Count  $\leftarrow 0$

for  $t \leftarrow 0$  to  $n$  do

if str[t] == start

for  $g \leftarrow t+1$  to  $n$  do

if str[g] == end

Count = Count + 1

operation with  
constant time

endif

endfor

endif

endfor

return Count

end

Time Complexity

$$T(n) = \sum_{t=0}^n \sum_{g=t+1}^n 1 = \sum_{t=0}^n n - (t+1) + 1 = \sum_{t=0}^n n - t = n + (n-1) + (n-2) + \dots + (n-n) \\ = \frac{n \cdot (n+1)}{2}$$

$$= \frac{n^2 + n}{2}$$

therefore,  
time complexity  
is

$\boxed{O(n^2)}$

5

Q4)

Algorithm closest-pair-brute-force (PointArray[(x<sub>0</sub>, y<sub>0</sub>), (x<sub>1</sub>, y<sub>1</sub>) .. (x<sub>n-1</sub>, y<sub>n-1</sub>)])

Keep = {}

Keep["point1"] ← PointArray[0]

Keep["point2"] ← PointArray[1]

Keep["dist"] ← sqrt((PointArray[1][0] - PointArray[0][0])\*\*2 + (PointArray[1][1] - PointArray[0][1])\*\*2)

for t ← 0 to n-1 do

for g ← t+1 to n do

dist ← sqrt((PointArray[t][0] - PointArray[g][0])\*\*2 + (PointArray[t][1] - PointArray[g][1])\*\*2)

if dist < Keep["dist"]

Keep["dist"] ← dist

Keep["point1"] ← PointArray[t]

Keep["point2"] ← PointArray[g]

endif

endfor

return Keep // it returns pair of points and its distance.

endfor

end

constant  
time  
operations

Time complexity Analysis

$$T(n) = \sum_{t=0}^{n-1} \sum_{g=t+1}^n 1 = \sum_{t=0}^{n-1} n - (t+1) + 1 = \sum_{t=0}^{n-1} n - t = n + (n-1) + \dots + 1$$

$$= \frac{n \cdot (n+1)}{2} = \frac{n^2 + n}{2}$$

Therefore,

time complexity =  $\boxed{O(n^2)}$

(6)

Q5)

a)

Algorithm mostProfitableClusters(clusters[0... n-1])

max ← 0

companies = []

for g ← 0 to n do

iter ← 0

for t ← g to n do

iter ← iter + clusters[t]

if iter &gt; max

max ← iter

operations with  
constant time

for i ← 0 to n

sum ← 0

for v ← i to n do

sum ← sum + clusters[v]

if sum == max

companies.append(clusters[i:v+1])

operations with  
constant time

return companies

// it returns the profit values of specific companies  
to identify them.Time complexity

$$T(n) = \sum_{g=0}^n \sum_{t=g}^n 1 + \sum_{i=0}^n \sum_{v=i}^n 1$$

$\rightarrow T_1(n)$                        $\rightarrow T_2(n)$

$$T_1(n) = \sum_{g=0}^n (n-g) + 1 = (n+1) + n + (n-1) + \dots + 1 = \frac{(n+1) \cdot (n+2)}{2} = \frac{n^2 + 3n + 2}{2}$$

$$T_2(n) = \sum_{i=0}^n (n-i) + 1 = (n+1) + n + (n-1) + \dots + 1 = \frac{(n+1) \cdot (n+2)}{2} = \frac{n^2 + 3n + 2}{2}$$

$$T(n) = T_1(n) + T_2(n) = 2 \cdot \left( \frac{n^2 + 3n + 2}{2} \right) = \frac{n^2 + 3n + 2}{1}$$

Therefore the time  
complexity is  $\rightarrow \boxed{O(n^2)}$

(7)

b)

Algorithm maximumProfit (profitArray[0... n-1], l ← None, r ← None)

left-iter ← 0

right-iter ← 0

summation ← 0

if n == 0 return 0

if r is None and l is None

l ← 0

r ← n-1

endif

if r == l

return profitArray[l]

endif

mid = (l + r) // 2

for i ← mid downto l-1 do  
 summation ← summation + profitArray[i]  
 if summation > left-iter  
 left-iter ← summation  
endfor  
summation ← 0

Operations with constant time. }  $\sum_{t=1}^{n/2} 1$

for i ← mid+1 to r+1 do  
 summation ← summation + profitArray[i]  
 if summation > right-iter  
 right-iter ← summation  
endif  
endfor  
maxKeep ← max(maximumProfit(profitArray, l, mid),  
maximumProfit(profitArray, mid+1, r))

Operations with constant time. }  $\sum_{t=1}^{n/2} 1$

return max(maxKeep, left-iter + right-iter)

end



8

$$T(n) = 2T(n/2) + \dots$$

$$\sum_{i=1}^{n/2} + \sum_{i=1}^{n/2} = 2 \sum_{i=1}^{n/2} = 2(n/2) = n //$$

first for loop → second for loop.

$$T(n) = 2T(n/2) + n \rightarrow f(n)$$

→ We can use master theorem to solve this recurrence relation!

$$\log_b^a = \log_2^2 = 1$$

$$\log_b^a = 1$$

$$f(n) = n \rightarrow n^k \log^p n \quad k=1 \text{ and } p=0$$

$$\log_b^a = 1 > \log_b^a = k \text{ and } p=0 > -1$$

so it's the first case of the case 2.  
Therefore, the time complexity is  $O(n^k \log^{p+1} n)$

$$k=1 \text{ and } p=0$$

$$O(n^1 \log^{0+1} n) \Rightarrow \boxed{O(n \log n)}$$

Result.

### Master Theorem

$$T(n) = aT(n/b) + f(n)$$

$$f(n) = O(n^k \log^p n)$$

$a \geq 1$   
 $b > 1$   
 $f(n)$  is asymptotically +

Case 1: If  $\log_b^a > k$  then  $O(n^{\log_b^a})$

Case 2: if  $\log_b^a = k$

i) if  $p > -1 \rightarrow O(n^k \log^{p+1} n)$

ii) if  $p = -1 \rightarrow O(n^k \log \log n)$

iii) if  $p < -1 \rightarrow O(n^k)$

Case 3:

if  $\log_b^a < k$

if  $p \geq 0 \rightarrow O(n^k \log^p n)$

if  $p < 0 \rightarrow O(n^k)$