

# 1. Description and Analysis of Divide and Conquer

*LS (left, right)* Find the maximum sum of contiguous elements of the array A between indices *left* and *right*.

```

if left = right then
    return (left, left, A[left])
end
middle ← floor of (left + right)/2
(start1, end1, sum1) ← LS(b, middle)
(start2, end2, sum2) ← LS(middle+1, e)
leftSum ← Double.MIN_VALUE
startPoint ← middle
sum ← 0
for i=middle to left do
    sum ← sum + A[i]
    if sum > leftSum then
        leftSum ← sum
        startPoint ← i
    end
end
rightSum ← Double.MIN_VALUE
endPoint ← middle+1
sum ← 0
for i = middle+1 to right do
    sum ← sum + A[i]
    if sum > rightSum then
        rightSum ← sum
        endPoint ← i
    end
end
sum3 ← rightSum + leftSum
if sum1 = max {sum1, sum2, sum3} then
    return (start1, end1, sum1)
end
if sum2 = max {sum1, sum2, sum3} then
    return (start2, end2, sum2)
end
else return (startPoint, endPoint, sum3)

```

Time complexity:

A call to this algorithm with an array of size  $n$  leads to two recursive calls on arrays of size  $n/2$ . Dividing the array has a constant cost. Computing the overall results from the sub results requires scanning the whole array and hence has a cost of  $\Theta(n)$ . The complexity is  $C(n) = 2C(n/2) + \Theta(n) = \Theta(n \log n)$

Space complexity:

No extra space required apart from making recursive stack calls, so space complexity is  $O(1)$ .

## 2. Description and Analysis of Dynamic Programming

*LS (left, right)* Find the maximum sum of contiguous elements of the array *A* between indices *left* and *right*.

```

if left = right then
    return (left, left, A[left])
end
listSum[0] ← A[left]
maxSum ← A[left]
for i=left+1 to right do
    if listSum[i-1] ≤ 0 then
        listSum[i] ← A[i]
    end
    if listSum[i-1] > 0 then
        listSum[i] ← listSum[i-1] + A[i]
    end
    if listSum[i] > maxSum then
        maxSum ← listSum[i]
        end ← i
    end
end
end
start ← end
for start = left+1 to end do
    if listSum[start-1] ≤ 0 then
        start = start+1
    end
end
return (maxSum, start, end)

```

Time complexity:

There are three independent iterations in a call to this algorithm with an array of size  $n$ , with each iteration having at most  $n$  steps. So, the time complexity is  $O(n)$ .

Space complexity:

Build an array to store maxSum for every  $i$ . Thus, space complexity is  $O(n)$ .

### 3. Graph



### 4. Observation about the empirical results

The empirical results correspond to the analysis.

The time complexity of divide and conquer algorithm is  $O(n \log n)$  which increases as the value of  $n$  increases. Because the time complexity of dynamic programming,  $O(n)$ , is linear, the running time of DC increases much more than DP when  $n$  increases.

### 5. Comparison of two algorithms

In term of time complexity, dynamic programming takes  $O(n)$  while divide and conquer takes  $O(n \log n)$ . Dynamic programming algorithm is much faster than divide and conquer. As we can see from the plots that DP algorithm is a lot faster in comparison to DC and the difference in time keeps on increasing as we keep on increasing the problem size.

In term of space complexity, dynamic programming takes  $O(n)$  while divide and conquer takes  $O(1)$ . Divide and conquer uses less space than dynamic programming.