CS 31: Algorithms (Spring 2019): Lecture 4

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Topic: Divide and Conquer 2: MaxRangeSubArray, Karatsuba Disclaimer: These notes have not gone through scrutiny and in all probability contain errors. Please email errors to deeparnab@dartmouth.edu.

1 Maximum Range Subarray

In this problem, we are given an array A[1 : n] of numbers (think integers or reals), and the goal is to find i < j such that A[j] - A[i] is maximized.

<u>MAXIMUM RANGE SUBARRAY</u> **Input:** Array A[1:n] of integers. **Output:** Indices $1 \le i \le j \le n$ such that A[j] - A[i] is maximized. **Size:** n, the length of A.

Once again, there is a trivial $O(n^2)$ time algorithm; go over all pairs (i, j) and choose the one that maximizes A[j] - A[i]. Once again, we think of a divide and conquer algorithm. Suppose we solved the problem on A[1 : n/2] and A[n/2 + 1 : n]. More precisely, suppose (i_1, j_1) was the MRS for A[1 : n/2] and (i_2, j_2) was the MRS for A[n/2 + 1 : n]. Clearly both of these are *candidate* or *feasible* solutions for A[1 : n].

Are there other candidate solutions? Yes, and these are of the form (i, j) with $i \le n/2$ and n/2 < j. Is it any easier to find such "cross" (i, j) pairs? In this case the answer is a resounding **yes!**: since we are trying to maximize A[j] - A[i], we should choose j which maximizes A[j] in $n/2 < j \le n$ and choose i such that A[i] is minimized in $1 \le i \le n/2$. These are O(n)-time operations; a win over $O(n^2)$!

> 1: procedure MRS0(A[1:n]): ▷ Returns $1 \le i \le j \le n$ maximizing A[j] - A[i]. 2: if n = 1 then: 3: $(i, j) \leftarrow (1, 1)$. \triangleright Singleton Array 4: 5: **return** (*i*, *j*). $m \leftarrow \lfloor n/2 \rfloor$ 6: 7: $(i_1, j_1) \leftarrow MRSO(A[1:m])$ $(i_2, j_2) \leftarrow MRSO(A[m+1:n])$ 8: $i_3 \leftarrow \arg\min_{1 \le t \le m} A[t] \triangleright \text{Takes } O(m) \text{ time}$ 9: $j_3 \leftarrow \arg \max_{m+1 \le t \le n} A[t] \triangleright \text{Takes } O(m) \text{ time}$ 10: return best among $(i_1, j_1), (i_2, j_2), (i_3, j_3)$. \triangleright Takes O(1) time 11:

As in merge-sort and counting inversions, if T(n) is the worst case running time of MRS0, then looking at the running time on the worst array of length n, we get

$$T(n) \le T(\lfloor n/2 \rfloor) + T(\lfloor n/2 \rfloor) + Oa(n)$$

which evaluates to $T(n) = \Theta(n \log n)$. This seems good, but in fact we can actually do better using a similar idea as discussed in counting inversions algorithm: Ask More!

If you "opened up" the recursion tree, you would observe that the $\Theta(n)$ time to compute the max's and the min's in Lines 9 and 10 seems repetitive; the same comparisons are made more than once. This gives an idea of what to ask more for; we want our maximum range sub-array algorithm *also* returns the maximum and minimum of that sub-array. This gives us the next algorithm.

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1: procedure MRS(A[1:n]):
 2:
         \triangleright Returns (s, t, i, j) where
        • A[j] - A[i] is maximized, and
        • s, t are the indices of the min and max of A, respectively.
         if n = 1 then:
 3:
              return (1, 1, 1, 1) \triangleright Singleton Array
 4:
 5:
         m \leftarrow \lfloor n/2 \rfloor
         (s_1, t_1, i_1, j_1) \leftarrow MRS(A[1:m])
 6:
         (s_2, t_2, i_2, j_2) \leftarrow MRS(A[m+1:n])
 7:
         s \leftarrow \arg\min(A[s_1], A[s_2]) and t \leftarrow \arg\max(A[t_1], A[t_2]). \triangleright Takes O(1) time
 8:
         (i, j) \leftarrow best solution among \{(i_1, j_1), (i_2, j_2), (s_1, t_2)\}. \triangleright Takes O(1) time
 9:
         return (s, t, i, j).
10:
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The conquer step in Line 8 takes only O(1) time: the max of the whole array is the max of the maxima in the two halves. Same for the minima. Therefore, the recurrence inequality becomes

 $T(n) \le T(\lceil n/2 \rceil) + T(\lfloor n/2 \rfloor) + O(1)$

solving which gives us the following.

Theorem 1. The MRS algorithm returns the maximum-range sub-array in $\Theta(n)$ time.

2 Multiplying Polynomials Faster: Karatsuba's Algorithm

Next we consider the problem of multiplying polynomials. The input is the (n + 1) coefficients of two univariate degree n polynomials p(x) and q(x) given as P[0:n] and Q[0:n]. That is,

$$p(x) = \sum_{i=0}^{n} P[i] \cdot x^{i}$$
 and $q(x) = \sum_{j=0}^{n} Q[j] \cdot x^{j}$

We desire to output the coefficients the polynomial $r(x) = p(x) \cdot q(x)$. Note that the degree of r(x) is 2n, and thus the coefficients needs to be stored in an array R[0 : 2n]. We also assume that every P[i], Q[j] are "small" numbers and so they can be added and multiplied in $\Theta(1)$ time¹.

An $O(n^2)$ time algorithm follows from the formula for R[k] which is as follows:

$$\forall 0 \le k \le 2n, \ R[k] = \sum_{\substack{0 \le i, j \le n: i+j=k}} P[i] \cdot Q[j] = \begin{cases} \sum_{\substack{0 \le i \le k}} P[i] \cdot Q[k-i] & \text{if } k \le n \\ \sum_{(k-n) \le i \le n} P[i] \cdot Q[k-i] & \text{if } n < k \le 2n \end{cases}$$

$$(1)$$

Do you see this? By the way, in signal processing this has another name. The array R[0:2n] is called the *convolution* of the two arrays P[0:n] and Q[0:n]. The above formula gives a $O(n^2)$ -time algorithm to compute the convolution.

We now show how Divide-and-Conquer gives a faster algorithm.

Remark: The story goes that in the early 1960s the famous Russian mathematician Andrei Kolmogorov held a seminar with the objective to show that any algorithm needs $\Omega(n^2)$ to multiply two degree *n* polynomials. After the first meeting, a young student named **Anatoly Karatsuba** came up with the algorithm we are about to describe. Kolmogorov canceled the remainder of the seminar.

Let $m = \lfloor n/2 \rfloor$. Consider the polynomial p(x) and write it as

$$p(x) = p_1(x) + x^m p_2(x)$$
 where $p_1(x) = \sum_{i=0}^{m-1} P[i]x^i$ and $p_2(x) = \sum_{i=0}^{n-m} P[m+i]x^i$ (2)

Similarly write

$$q(x) = q_1(x) + x^m q_2(x)$$
 where $q_1(x) = \sum_{j=0}^{m-1} Q[j] x^j$ and $q_2(x) = \sum_{j=0}^{n-m} Q[m+j] x^j$ (3)

This gives us the following formula for $r(x) = p(x) \cdot q(x)$.

$$r(x) = (p_1(x) + x^m p_2(x)) \cdot (q_1(x) + x^m q_2(x))$$

= $(p_1(x) \cdot q_1(x)) + x^m \cdot (p_1(x) \cdot q_2(x) + p_2(x) \cdot q_1(x)) + x^{2m} \cdot (p_2(x) \cdot q_2(x))$ (4)

Now note that all four polynomials $p_1(x)$, $p_2(x)$, $q_1(x)$, $q_2(x)$ have degree $\leq \lceil n/2 \rceil$. Therefore, (4) implies that r(x) can be computed by recursively multiplying the four pairs $(p_1(x), q_1(x)), (p_1(x), q_2(x)), (p_2(x), q_1(x)), \text{ and } (p_2(x), q_2(x))$. Subsequently, we need to add these polynomials up, but adding polynomials is a simple $\Theta(n)$ operation.

¹If they are *d*-digits, this is what was studied in the Supplemental Problem : Number Theory set – take a look.

To sum, the above recursive algorithm has the following recurrence inequality: $T(n) \le 4T(\lceil n/2 \rceil) + \Theta(n)$. We apply the Master Theorem and get $T(n) = O(n^2)$. Sigh! Much ado about nothing?

Next comes the Aha! insightful observation. We observe that we really don't need the individual products $p_1(x) \cdot q_2(x)$ and $p_2(x) \cdot q_1(x)$; rather we need just their sum.

Observation 1.

$$p_1(x)q_2(x) + p_2(x)q_1(x) = \left(p_1(x) + p_2(x)\right) \cdot \left(q_1(x) + q_2(x)\right) - \left(p_1(x) \cdot q_1(x)\right) - \left(p_2(x) \cdot q_2(x)\right)$$

Therefore, the (4) can be computed using 3 multiplication of polynomials of degree $\lceil n/2 \rceil$. These three are $(p_1(x) \cdot q_1(x))$, $(p_2(x) \cdot q_2(x))$, and $((p_1(x) + p_2(x)) \cdot (q_1(x) + q_2(x)))$. After computing this, the polynomial r(x) can be computed using (4) and Observation 1 with $\Theta(1)$ polynomial additions and subtractions. Now, the recurrence inequality governing the above algorithm becomes

$$T(n) \le 3T(\lceil n/2 \rceil) + \Theta(n)$$

which gives us the following.

Theorem 2. The algorithm KARATMULTPOLY multiplies two *n*-degree univariate polynomials in $O(n^{\log_2 3}) = O(n^{1.59})$ time.

1: procedure KARATMULTPOLY(P[0:n], Q[0:n]):> We want to return R[0:2n]. if n = 0, 1 then: 2: **return** R[0:2n] using the naive multiplication 3: $m = \lceil n/2 \rceil.$ 4: \triangleright Recall definitions of $p_1(x), p_2(x), q_1(x), q_2(x)$ from (2),(3) 5: for $0 \le i \le m - 1$ do 6: P'[i] = (P[i] + P[m+i])7: 8: Q'[i] = (Q[i] + Q[m+i])9: if n > 2m - 1 then: \triangleright In which case n = 2m since m = n/2 or m = (n + 1)/2. P'[m] = P[n]10: Q'[m] = Q[n]11: 12: else: P'[m] = Q'[m] = 013: \triangleright Now P' has the coefficients of $p_1(x) + p_2(x)$. Q' has the coefficients of $q_1(x) + q_2(x)$. 14: \triangleright Their degrees are m-1 or m depending on the parity of n. 15: \triangleright The else statement above forces degree m. 16: 17: $R_1[0:2(m-1)] = \text{KARATMULTPOLY}(P[0:m-1],Q[0:m-1])$ 18: $R_2[0:2(n-m)] = \text{KARATMULTPOLY}(P[m:n], Q[m:n])$ 19: $R_3[0:2m] = \text{KARATMULTPOLY}(P'[0:m], Q'[0:m])$ 20: $\triangleright R_1$ has the coefficients of $p_1(x) \cdot q_1(x)$ 21: $\triangleright R_2$ has the coefficients of $p_2(x) \cdot q_2(x)$ 22: $\triangleright R_3$ has the coefficients of $(p_1(x) + p_2(x)) \cdot (q_1(x) + q_2(x))$ 23: \triangleright Also note that R_1, R_2, R_3 all have length $\leq 2m$. We assume they all are 2m length 24: by padding 0's. for $0 \le i \le 2m$ do: 25: $R_4[i] = (R_3[i] - R_1[i] - R_2[i])$ 26: $\triangleright R_4$ has the coefficients of $p_1(x) \cdot q_2(x) + p_2(x) \cdot q_1(x)$ and is degree 2m27: for 0 < i < 2n do: 28: 29: $R[i] = R_1[i] + R_4[i-m] + R_2[i-2m]$ \triangleright We assume an array 'returns 0' if indexed out of its range. For instance, $R_4[-1]$ 30: returns 0 and $R_1[2n]$ returns 0. ▷ When you actually code it, you need a few "if" statements to implement the 31: above. A drill will ask you to do this. Please do that – it's super instructive. return R[0:2n]32: