## INT102 Lec 3 Divide and Conquer

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Recursive Binary Search
       BINARY-SEARCH-RECURSIVE(A, v, low, high)
           if low > high return false
           mid = \lfloor (low + high) / 2 \rfloor
       3
           if v > A[mid]
       4
                return BINARY-SEARCH-RECURSIVE(A, v, mid + 1, high)
       5
           else if v < A[mid]
                return BINARY-SEARCH-RECURSIVE(A, v, low, mid - 1)
       6
           else return mid
Time Complexity of binary search algorithm on n numbers:
                   if n = 1,
               \begin{cases} T(n/2) + 1 & \text{otherwise.} \end{cases}
       We call this formula a recurrence.
Recurrence
       A recurrence is an equation or inequality that describes a function
       interns of its value on smaller inputs.
       To solve a recurrence is to derive asymptotic bounds on the
       solution.
Substitution Method
       1. Make a guess (for example: T(n) \le 2 \log n)
       Prove statement by mathematic induction:
              Assume true for all n' < n [Assume T(n/2) \le 2\log(n/2)]
                      T(n) = T(n/2) + 1
                           \leq 2\log(n/2) + 1
                           = 2(\log n - 1) + 1
                           < 2 \log n,
               it follows that \log(n/2) = \log n - \log 2.
              Hence T(n) = O(\log n).
       Example:
               Prove that T(n) = \begin{cases} 1 & \text{if } n = 1, \\ 2T(n/2) + 1 & \text{otherwise.} \end{cases} is O(n).
               Guess: T(n) \leq 2n - 1,
               Assume true for all n' < n s.t.
                      T(n) = 2T(n/2) + 1
                           \leq 2(2*(n/2)-1)+1
                           =2n-2+1
                           =2n-1,
              Hence, T(n) = O(n).
       Example 2:
               Prove that T(n) = \begin{cases} 1 & \text{if } n = 1, \\ 2T(n/2) + n & \text{otherwise.} \end{cases} is O(n \log n).
               Guess: T(n) \le 2n \log n
               Assume true for all n' < n s.t.
                      T(n) = 2T(n/2) + n
                           < 2(2(n/2)\log(n/2)) + n
                           = 2n(\log n - 1) + n
                           = 2n \log n - 2n + n
                           \leq 2n \log n,
              Hence T(n) = O(n \log n).
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Depending on recurrence we observe:
                 T(n) = T(n/2) + \Theta(1),
                                                    T(n) = O(\log n);
                 T(n) = 2T(n/2) + \Theta(1),
                                                    T(n) = O(n);
                 T(n) = 2T(n/2) + \Theta(n),
                                                    T(n) = O(n \log n).
Merge Sort
        MERGE-SORT(A[0 ... n-1])
             if n > 1 then
        2
                  copy A[0 ... | n/2 | -1] to B[0 ... | n/2 | -1]
        3
                  copy A[ | n/2 | ... n-1 ] to C[0 ... [n/2] -1 ]
                  MERGE-SORT(B[0 ... | n/2 | -1])
        4
         5
                  MERGE-SORT(C[0 ... [n/2] - 1])
                  MERGE(B, C, A)
         T_{\text{MergeSort}}(n) = \Theta(1) + \Theta(n/2) + \Theta(n/2) + T_{\text{MergeSort}}(\lfloor n/2 \rfloor) + T_{\text{MergeSort}}(\lceil n/2 \rceil) + T_{\text{Merge}}(n)
               = 2 T_{\text{MergeSort}}(n/2) + \Theta(n)
               =\Theta(n \log n)
        MERGE(B[0 ... p-1], C[0 ... q-1], A[0 ... p+q-1])
             Set i = 0, j = 0, k = 0
        2
             while i < p and j < q do
        3
                                         set A[k] = B[i], and i = i + 1
                  if B[i] \leq C[j] then
         4
                                         set A[k] = C[j], and j = j + 1
        5
                  k = k + 1
        6
             if i == p then
                                copy C[j ... q - 1] to A[k ... p + q - 1]
                                copy B[i ... p - 1] to A[k ... p + q - 1]
             else
         T_{\text{Merge}}(n) = \Theta(n)
Time Complexity of Merge Sort
         It costs \Theta(n) time to MERGE, plus two T_{\mathrm{MergeSort}}(n/2) recursive calls of
        \ensuremath{\mathsf{MERGE}\text{-}}\ensuremath{\mathsf{SORT}}\xspace , giving the following recurrence:
                 T(n) = \begin{cases} 1 & \text{if } n = 1, \\ 2T(n/2) + \Theta(n) & \text{otherwise,} \end{cases}
        hence, T(n) = O(n \log n).
The master method for solving recurrences:
        Master Theorem:
                 Let a \ge 1 and b \ge 1 be constants, let f(n) be a function, and let
                 T(n) be defined on the non negative integers by the recurrence:
                          T(n) = aT(n/b) + f(n)
                 where n/b can be interpreted as either \lfloor x/b \rfloor and \lceil x/b \rceil.
                 Then T(N) has the following asymptotic bounds:
                 1. If f(n) = O(n^{\log_b a - \epsilon}) for some constant \epsilon > 0, then T(n) = \Theta(n^{\log_b a}).
                 2. If f(n) = \Theta(n^{\log_b a}), then T(n) = \Theta(n^{\log_b a} \lg n).
                 3. If f(n) = \Omega(n^{\log_b a + \epsilon}) for some constant \epsilon > 0, then T(n) = \Theta(f(n)).
T(n) = T(n/2) + \Theta(n):
        Let a = 1, b = 2, f(n) = \Theta(n), then \log_b a = \log_2 1 = 0.
         If we pick \epsilon = 1, then f(n) = \Omega(n^{\log_b a + \epsilon}) = \Omega(n^{0+1}).
        Hence using Master's Theorem, it follows that T(n) = \Theta(f(n)) = \Theta(n).
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