

CSC236H

Introduction to the Theory of Computation

Running-Time Complexity of Algorithms - Review

- Measure running time by counting **steps** in algorithm: arithmetic operations, assignments, array accesses, comparisons, return statements, etc.
- Measure as a function $T(n)$ of **input size** n .
- $T(n)$ measures worst-case running time: maximum number of steps over all inputs of size n .
- We don't care about exact step counts, an estimate for $T(n)$ is sufficient:
 - every **chunk** of instructions is represented by a constant.
 - **chunk**: sequence of instructions that always gets executed together.
- Most of the time, NO simple algebraic expression for $T(n)$. Instead we prove bounds on $T(n)$, using asymptotic notation.
- **Upper bound**: $T(n) \in \mathcal{O}(f(n))$.
- **Lower bound**: $T(n) \in \Omega(f(n))$.
- **Tight bound**: $T(n) \in \Theta(f(n))$:
 $T(n) \in \mathcal{O}(f(n))$ and $T(n) \in \Omega(f(n))$.

- If $T(n)$ is a **polynomial** of degree k , then $T(n) \in \mathcal{O}(n^k)$.
- An $\mathcal{O}(1)$ algorithm is **more** efficient than an $\mathcal{O}(\log n)$ algorithm,
which is **more** efficient than an $\mathcal{O}(n)$ algorithm,
which is **more** efficient than an $\mathcal{O}(n \log n)$ algorithm,
which is **more** efficient than an $\mathcal{O}(n^2)$ algorithm,
which is **more** efficient than an $\mathcal{O}(2^n)$ algorithm.
- If $T(n) = g(n) + f(n)$, and $f(n)$ is **less** efficient than $g(n)$, then $T(n) \in \mathcal{O}(f(n))$.

""" Given a list A, return an index i such that $x == A[i]$.
Otherwise, return -1. """

```
def LS(A,x):  
1.     i = 1  
2.     while i < len(A):  
3.         if A[i] == x:  
4.             return i  
5.         i = i + 1  
6.     return -1
```

```
""" Given a natural number  $n \geq 1$ , return  $n!$  """  
def fact(n):  
    1.    if n == 1:  
    2.        return 1  
    3.    else:  
    4.        return n * fact(n-1)
```

A **closed-form** formula:

- allows to calculate a function by applying a **fixed** number of **basic** operations to its argument(s):
 - Basic Operations: addition, subtraction, multiplication, division, and exponentiation.
- $n^3 + n - 1$.
- $1 + 2 + \dots + n$.
- $f(n - 1) + f(n - 2)$.

$$T(n) = \begin{cases} a & n = 1 \\ b + T(n - 1) & n \geq 2 \end{cases}$$

$$f(n) = \begin{cases} 0 & n = 0 \\ f(n-1) + 2n - 1 & n \geq 1 \end{cases}$$

Example – Running-Time Complexity of Recursive Binary Search

```
""" Given a sorted list A of length at least 1, return t such that
start <= t <= end and A[t] == x, if such a t exists;
otherwise return -1."""
def RecBinSearch(A, start, end, x):
1.   if (start == end) then:
2.       if (A[start] == x) then:
3.           return start
4.       else:
5.           return -1
6.   else:
7.       m = (start + end) // 2           # integer division
8.       if (A[m] >= x) then:
9.           return RecBinSearch(A, start, m, x)
10.      else:
11.          return RecBinSearch(A, m + 1, end, x)
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```

$$T(n) = \begin{cases} a & n = 1 \\ T(\frac{n}{2}) + b & n \geq 2 \end{cases}$$

IMPORTANT: In asymptotic analysis, we may ignore floors and ceilings.

Thus, we may always assume that the size of the input is so that the recursive calls always divide the input list evenly. (Take Home Exercise: convince yourself why)

→ In the running-time analysis of binary search, we assume that n is a power of 2:

There exists some j s.t. $n = 2^j$.

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Example – Running-Time Complexity of Merge Sort

```
""" Given a non-empty list A, sort the list in non-decreasing order. """
def MergeSort(A):
    2.     if len(A) == 1:
    3.         return A
    4.     else:
    5.         m = len(A) // 2 # integer division
    6.         L1 = MergeSort(A[0..m-1])
    7.         L2 = MergeSort(A[m..len(A)-1])
    8.         return merge(L1, L2)
def merge(A, B):
    9.     i = 0
    10.    j = 0
    11.    C = []
    12.    while (i < len(A)) and (j < len(B)):
    13.        if (A[i] <= B[j]):
    14.            C.append(A[i]) # Add A[i] to the end of C
    15.            i += 1
    16.        else:
    17.            C.append(B[j])
    18.            j += 1
    19.    return C + A[i..len(A)-1] + B[j..len(B)-1] # List concatenation
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    19.    return C + A[i..len(A)-1] + B[j..len(B)-1] # List concatenation
```

$$T(n) = \begin{cases} a & n = 1 \\ 2T(\frac{n}{2}) + bn & n \geq 2 \end{cases}$$

$$T(n) = \begin{cases} a & n = 1 \\ cT(\frac{n}{d}) + bn^k & n \geq 2 \end{cases}$$

- $x^{a \times b} = (x^a)^b$.
- If $z = \log_x y$, then $x^z = y$.
- $x^{\log_x y} = y$.

$$T(n) = \begin{cases} a & n = 1 \\ c T(\frac{n}{d}) + bn^k & n \geq 2 \end{cases}$$

Theorem (Master Theorem). Let $T : \mathbb{N} \rightarrow \mathbb{R}^+$ be a recursively defined function with recurrence relation

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

for some constants $c, d \in \mathbb{Z}^+$, $d > 1$, and $f : \mathbb{N} \rightarrow \mathbb{R}^+$.

Furthermore, suppose $f(n) \in \Theta(n^k)$ for some $k \in \mathbb{R}, k \geq 0$. Then:

1. if $k = \log_d c$, then $T(n) \in \mathcal{O}(n^k \log n)$;
2. if $k < \log_d c$, then $T(n) \in \mathcal{O}(n^{\log_d c})$;
3. if $k > \log_d c$, then $T(n) \in \mathcal{O}(n^k)$.

Example – Applying the Master Theorem

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• **Example:** Recursive Binary Search:

$$T(n) = \begin{cases} a, & n = 1 \\ T(\frac{n}{2}) + b, & n \geq 2 \end{cases}$$

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• **Example:** Merge Sort:

$$T(n) = \begin{cases} a, & n = 1 \\ T\left(\frac{n}{2}\right) + bn, & n \geq 2 \end{cases}$$

Theorem (Master Theorem). Let $T : \mathbb{N} \rightarrow \mathbb{R}^+$ be a recursively defined function with recurrence relation

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• **Example:** $T(n) = 9T\left(\frac{n}{3}\right) + 100n\sqrt{2}$.

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Furthermore, suppose $f(n) \in \Theta(n^k)$ for some $k \in \mathbb{R}, k \geq 0$. Then:

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3. if $k > \log_d c$, then $T(n) \in \mathcal{O}(n^k)$.

- **Example:** $T(n) = 10T\left(\frac{n}{4}\right) + 10n^\pi$.