CS217 - Data Structures & Algorithm Analysis (DSAA)

Lecture #3

Divide-and-Conquer

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Reading: Section 2.3 and Section 4.5

(optional: lots more details in Chapter 4)

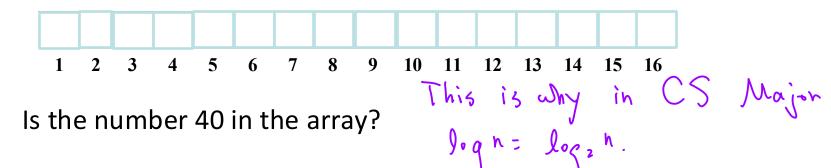
Aims of this lecture

- To introduce the divide-and-conquer design paradigm.
- To introduce the MergeSort algorithm a recursive algorithm using divide-and-conquer.

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- To show how to prove correctness for a recursive algorithm
- To show how to analyse the runtime of recursive algorithms using recurrence equations.
- To show how to solve recurrence equations

Problem: Find a number in a sorted array

• I have a sorted array of integers;



- If we scan the array from the beginning to the end what is the worst case runtime? $\theta(n)$ linear search
- What if we always check the middle point and discard the "wrong" half of the subarray? $2^k = n \Rightarrow \theta(\log n) binary search$
- By dividing the problem size by half at each step we have reduced the runtime of the algorithm from linear to logarithmic!

Design Paradigms

- InsertionSort used an incremental approach:
 - Having sorted the subarray A[1..j-1], we inserted A[j] into its proper place, yielding the sorted subarray A[1..j].
 - Idea: incrementally build up a solution to the problem.
- Alternative design approach: divide-and-conquer
 - 1. **Divide:** Break the problem into smaller subproblems, smaller instances of the original problem.
 - **2. Conquer:** Solve these problems recursively.
 - **3. Combine** the solutions to subproblems into the solution for the original problem.



MergeSort

- MergeSort sorting using divide-and-conquer:
 - 1. Divide the n-element sequence to be sorted into two subsequences of n/2 elements each.
 - **2. Conquer:** Sort the two subsequences **recursively** using MergeSort.
 - **3. Combine: merge** the two subsequences to produce the sorted answer.
 - The recursion stops when the sequence is just 1 element.
 - Key here is the procedure Merge
 - Tedious bit: copying elements between arrays.

Merge(A, p, q, r)

- Assume subarrays $A[p \dots q]$ and $A[q+1 \dots r]$ are sorted.
- Copy these subarrays to new arrays L and R.
- Merge L and R back into A by comparing L[i] and R[j].

```
Merge(A, p, q, r)
 1: n_1 = q - p + 1
 2: n_2 = r - q
 3: let L[1...n_1+1] and R[1...n_2+1] be new arrays
                                                          Set up arrays L
 4: for i = 1 to n_1 do
   L[i] = A[p+i-1]
                                                          and R (boring)
 6: for j = 1 to n_2 do
   R[j] = A[q+j]
 8: L[n_1+1]=\infty
 9: R[n_2+1]=\infty
10: i = 1
11: j = 1
12: for k = p to r do
        if L[i] \leq R[j] then
13:
                                                          Actual merge
            A[k] = L[i]
14:
            i = i + 1
15:
      \mathbf{else}
16:
            A[k] = R[j]
17:
            j = j + 1
18:
```

MERGE(A, p, q, r)New book pseudo-code without sentinels

```
1 n_L = q - p + 1 // length of A[p:q]
 2 \quad n_R = r - q \qquad \qquad \text{// length of } A[q+1:r]
 3 let L[0:n_L-1] and R[0:n_R-1] be new arrays
 4 for i = 0 to n_L - 1 // copy A[p:q] into L[0:n_L - 1]
 5 	 L[i] = A[p+i]
 6 for j = 0 to n_R - 1 // copy A[q + 1:r] into R[0:n_R - 1]
       R[j] = A[q + j + 1]
 8 i = 0 // i indexes the smallest remaining element in L
 9 j = 0 // j indexes the smallest remaining element in R
              # k indexes the location in A to fill
10 k = p
11 // As long as each of the arrays L and R contains an unmerged element,
          copy the smallest unmerged element back into A[p:r].
12 while i < n_L and j < n_R
       if L[i] < R[j]
13
   A[k] = L[i]
14
15 i = i + 1
16 else A[k] = R[j]
17
   i = i + 1
       k = k + 1
18
    // Having gone through one of L and R entirely, copy the
    " remainder of the other to the end of A[p:r].
   while i < n_L
20
   A[k] = L[i]
21
   i = i + 1
22
23 	 k = k + 1
24 while j < n_R
25 	 A[k] = R[j]
26 	 j = j + 1
27 	 k = k + 1
```



Runtime of Merge

 $T(n) = \Theta(n)$

Merge(A, p, q, r)

```
1: n_1 = q - p + 1
 2: n_2 = r - q
 3: let L[1 \dots n_1 + 1] and R[1 \dots n_2 + 1] be new arrays
 4: for i = 1 to n_1 do
 5: L[i] = A[p+i-1]
                                  \Theta(n)
 6: for j = 1 to n_2 do
 7: R[j] = A[q+j]
8: L[n_1+1]=\infty
9: R[n_2+1]=\infty
10: i = 1
                                         only 1 loop
11: j = 1
12: for k = p to r do
                                   \Theta(n)
        if L[i] \leq R[j] then
13:
             A[k] = L[i]
14:
            i = i + 1
15:
   \mathbf{else}
16:
             A[k] = R[j]
17:
             j = j + 1
18:
```

Set up arrays L and R (boring)

Actual merge

Correctness of Merge (1)

- Loop invariant: At the start of the iteration of the last for loop,
 - the subarray $A[p\dots k-1]$ contains the k-p smallest elements of $L[1\dots n_1+1]$ and $R[1\dots n_2+1]$, in sorted order and
 - L[i] and R[j] are the smallest elements of their arrays that have not been copied back to A.
- Initialisation: the loop starts with k=p, hence A[p ... k-1] is empty and contains the k-p=0 smallest elements of L,R. As i=j=1, L[i] and R[j] are the smallest uncopied elements.

Correctness of Merge (2)

- Loop invariant: At the start of the iteration of the last for loop,
 - the subarray $A[p\dots k-1]$ contains the k-p smallest elements of $L[1\dots n_1+1]$ and $R[1\dots n_2+1]$,in sorted order and
 - L[i] and R[j] are the smallest elements of their arrays that have not been copied back to A.
- Maintenance: suppose $L[i] \leq R[j]$.Then L[j] is the smallest element not copied back. $A[p \dots k-1]$ contains the k-p smallest elements, and after copying L[j] into $A[k], A[p \dots k]$ contains the k-p+1 smallest elements. Incrementing k and j reestablishes the loop condition.

Argue similarly for R[j] < L[i].

Correctness of Merge (3)

- Loop invariant: At the start of the iteration of the last for loop,
 - the subarray $A[p\dots k-1]$ contains the k-p smallest elements of $L[1\dots n_1+1]$ and $R[1\dots n_2+1]$, in sorted order and
 - L[i] and R[i] are the smallest elements of their arrays that have not been copied back to A.
- **Termination:** at termination, k=r+1. By the loop invariant, $A[p \dots k-1]=A[p \dots r]$ contains the $k-p=r-p+1=n_1+n_2$ smallest elements of $L[1 \dots n_1+1]$ and $R[1 \dots n_2+1]$, in sorted order. That's all elements in L and R apart from the two ∞ .

MergeSort: The Complete Algorithm

Notation: $\lfloor x \rfloor$ means "floor of x" (rounding down).

```
MERGESORT(A, p, r)
```

```
1: if p < r then
2: q = |(p+r)/2|
```

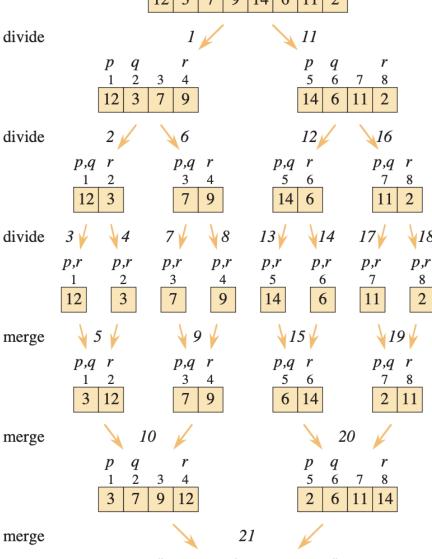
- 3: MERGESORT(A, p, q)
- 4: MERGESORT(A, q + 1, r)
- 5: MERGE(A, p, q, r)

Initial call: MERGESORT(A, 1, A.length)

Operation of MergeSort

MergeSort(A, p, r)

- 1: if p < r then
- $2: q = \lfloor (p+r)/2 \rfloor$
- 3: MERGESORT(A, p, q)
- 4: MERGESORT(A, q + 1, r)
- 5: MERGE(A, p, q, r)



5 6

Correctness of MergeSort

$\frac{\text{MERGESORT}(A, p, r)}{1: \text{ if } p < r \text{ then}}$ $2: \quad q = \lfloor (p + r)/2 \rfloor$ $3: \quad \text{MERGESORT}(A, p, q)$ $4: \quad \text{MERGESORT}(A, q + 1, r)$ $5: \quad \text{MERGE}(A, p, q, r)$

Proof by Induction:

Weak induction

- Base case: Show statement true for initial case: n=a (usually n=0 or n=1)
- Inductive step: If assumed true for n and can show true for n+1 then true for all $n \ge a$

Strong induction

- Base case: Show statement true for initial case: n=a (usually n=0 or n=1)
- Inductive step: If assumed true for $a \le k \le n$ and can show true for n+1 then true for all $n \ge a$

Strong induction can be proved using Weak induction

Correctness of MergeSort

Proof by Induction:

```
MERGESORT(A, p, r)

1: if p < r then

2: q = \lfloor (p+r)/2 \rfloor

3: MERGESORT(A, p, q)

4: MERGESORT(A, q+1, r)

5: MERGE(A, p, q, r)
```

Assume MergeSort sorts correctly arrays of size < n and show that it sorts correctly an array of size n

- Base case: n=1 => the algorithm returns at line 1 with the sorted array
 of a single element
- **Inductive step:** by inductive assumption lines 3 and 4 return two subarrays sorted correctly. We have already proved that **Merge** is correct hence after its execution the algorithm will return the array A sorted

MergeSort: Runtime Analysis

- Looking for time T(n): time for MergeSort to sort n elements.
- Assume for simplicity that n is an exact power of 2.

$\overline{\mathrm{MergeSort}(A,p,r)}$			Time for
1: if $p < r$ then		$\Theta(1)$	MergeSort
2:	$q = \lfloor (p+r)/2 \rfloor$	$\Theta(1)$	to sort n/2 elements.
3:	MergeSort(A, p, q)	T(n/2)	elements.
4:	MERGESORT(A, q + 1, r)	T(n/2)	
5:	$\mathrm{Merge}(A,p,q,r)$	$\Theta(n)$	

Yields a recurrence equation where T(n) depends on T(n/2):

• If n=1, then p=r, and the algorithm terminates in constant time $\Theta(1)$

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 2^0 = 1\\ 2T(n/2) + \Theta(n) & \text{if } n = 2^k, \text{ for } k \ge 1 \end{cases}$$

• "The time for MergeSort to sort n elements is twice the time for MergeSort to sort n/2 elements plus $\Theta(n)$ time (for Merge)."

Recurrence Equation (MergeSort)

- Looking for time T(n): time for MergeSort to sort n elements.
- Assume for simplicity that n is an exact power of 2.

MergeSort(A, p, r)		Time	Time for
1: if $p < r$ then		$\Theta(1)$	MergeSort
2:	$q = \lfloor (p+r)/2 \rfloor$	$\Theta(1)$	to sort n/2 elements.
3:	MergeSort(A, p, q)	T(n/2)	Cicinents.
4:	MERGESORT $(A, q + 1, r)$	T(n/2)	
<u>5:</u>	Merge(A, p, q, r)	$\Theta(n)$	

Yields a recurrence equation where T(n) depends on T(n/2):

- If n=1, then p=r, and the algorithm terminates in constant time $\Theta(1)$
- Otherwise: T(n) = D(n) + a T(n/b) + C(n)
 - D(n) time to *divide* into subproblems: $\Theta(1)$
 - a T(n/b) time to solve <u>a subproblems</u> each of size n/b: 2 T(n/2)
 - C(n) time to *conquer* (to combine the obtained sub-solutions): $\Theta(n)$

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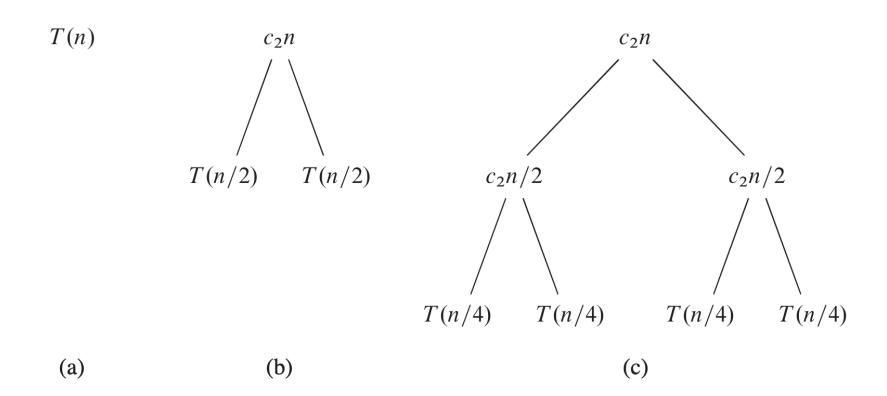
How to Solve a Recurrence Equation

$$T(n) = \begin{cases} d & \text{if } n = 2^{0} \\ 2T(n/2) + cn & \text{if } n = 2^{k}, \text{ for } k \ge 1 \end{cases}$$

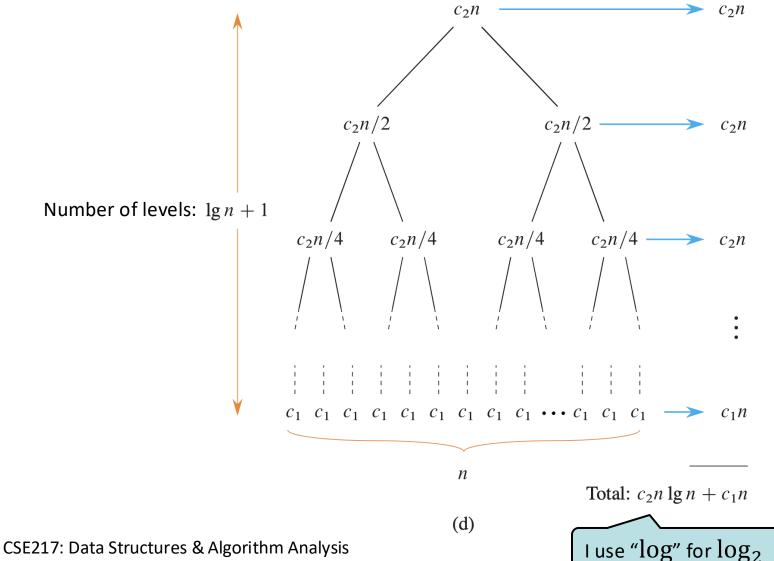
- **1. Substitution method** (Sec 4.3): guess a solution and verify using **induction** (over *k*).
 - Tutorial exercise.
- 2. Draw a recursion tree (Sec 4.4), add times across the tree.
- 3. Use the **Master Theorem** (Sec 4.5) to solve a general recurrence equation in the shape of:

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

Runtime Visualised as Recursion Tree



Runtime Visualised as Recursion Tree



Comparison with InsertionSort

- MergeSort always runs in time $\Theta(n \log n)$.
- Way better than worst case and average case of $\Theta(n^2)$ for InsertionSort.
- Worse than the best-case time $\Theta(n)$ of InsertionSort.
 - InsertionSort might be faster if your array is almost sorted.
- MergeSort needs more space than InsertionSort:
 - MergeSort always stores $\Omega(n)$ elements outside the input.
 - InsertionSort only needs O(1) additional space.
 - We say that InsertionSort sorts in place:

A sorting algorithm sorts in place if it only uses O(1) additional space.

The Master Theorem (1)

- Provides a "cookbook" method for solving recurrences of the form T(n)=aT(n/b)+f(n) where a>0 and b>1
- f(n) is called the driving function and T(n) is called the master recurrence
- The master recurrence T(n) describes the running time of a divide and conquer algorithm that divides a problem of size n into a subproblems each of size n/b < n
 - -> the algorithm solves each subproblem in time T(n/b)
- The driving function f(n) describes the cost of dividing the problem before the recursion (divide), as well as the cost of combining the results together (conquer)

Important term:

• $n^{\log_b a}$ is called the watershed function

The Master Theorem (Statement)

Let a > 0 and b > 1 be constants, and let f(n) be non-negative for large enough n. Then, the solution of the recurrence function defined over $n \in \mathbb{N}$

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

has the following asymptotic behaviour:

- 1. If there exists a constant $\epsilon > 0$ such that $f(n) = O(n^{\log_b a \epsilon})$, then $T(n) = \Theta(n^{\log_b a})$.
- 2. If there exists a constant $k \ge 0$ such that $f(n) = \Theta(n^{\log_b a} \lg^k n)$, then $T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$.
- 3. If there exists a constant $\epsilon > 0$ such that $f(n) = \Omega(n^{\log_b a + \epsilon})$, and if f(n) additionally satisfies the *regularity condition* $af(n/b) \le cf(n)$ for some constant c < 1 and all sufficiently large n, then $T(n) = \Theta(f(n))$.

The Master Theorem (Properties)

 Allows you to state the master recurrence T(n) without floors and ceilings even when you don't have problems of exactly the same size

eg.,
$$T(n) = T(\left\lceil \frac{n}{2} \right\rceil) + T(\left\lceil \frac{n}{2} \right\rceil) + \theta(n)$$

 The theorem does not apply to all possible recurrence equations but it does cover the vast majority of those that arise in practice

> The Master Theorem: closer look

- 1. If there exists a constant $\epsilon > 0$ such that $f(n) = O(n^{\log_b a \epsilon})$, then $T(n) = \Theta(n^{\log_b a})$.
- 2. If there exists a constant $k \ge 0$ such that $f(n) = \Theta(n^{\log_b a} \lg^k n)$, then $T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$.
- 3. If there exists a constant $\epsilon > 0$ such that $f(n) = \Omega(n^{\log_b a + \epsilon})$, and if f(n) additionally satisfies the *regularity condition* $af(n/b) \le cf(n)$ for some constant c < 1 and all sufficiently large n, then $T(n) = \Theta(f(n))$.
- $n^{\log_b a}$ is called the watershed function
- Case 1: the watershed function must grow polynomially faster than f(n) by at least a factor $\theta(n^{\epsilon})$ for some constant $\epsilon > 0$
- Case 2: watershed and driving (f(n)) functions grow asymptotically nearly at the same rate (you get the same growth for k = 0 common situation)
- Case 3: the watershed function must grow polynomially slower than f(n) by at least a factor $\theta(n^{\epsilon})$ for some constant $\epsilon>0$ + regularity condition must hold

The Master Theorem: MergeSort example

- 1. If there exists a constant $\epsilon > 0$ such that $f(n) = O(n^{\log_b a \epsilon})$, then $T(n) = \Theta(n^{\log_b a})$.
- 2. If there exists a constant $k \ge 0$ such that $f(n) = \Theta(n^{\log_b a} \lg^k n)$, then $T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$.
- 3. If there exists a constant $\epsilon > 0$ such that $f(n) = \Omega(n^{\log_b a + \epsilon})$, and if f(n) additionally satisfies the *regularity condition* $af(n/b) \le cf(n)$ for some constant c < 1 and all sufficiently large n, then $T(n) = \Theta(f(n))$.
- MergeSort: $T(n) = 2T(n/2) + \theta(n)$
- a=2, b=2, f(n) = θ (n) watershed function: $n^{\log_b a} = n^{\log_2 2} = n^1 = n$
- Does Case 1 hold? Does the watershed function grow polynomially faster than f(n)?
- Does Case 3 hold? Does the watershed function grow polynomially slower than f(n)?

> The Master Theorem: MergeSort example

- 1. If there exists a constant $\epsilon > 0$ such that $f(n) = O(n^{\log_b a \epsilon})$, then $T(n) = \Theta(n^{\log_b a})$.
- 2. If there exists a constant $k \ge 0$ such that $f(n) = \Theta(n^{\log_b a} \lg^k n)$, then $T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$.
- 3. If there exists a constant $\epsilon > 0$ such that $f(n) = \Omega(n^{\log_b a + \epsilon})$, and if f(n) additionally satisfies the *regularity condition* $af(n/b) \le cf(n)$ for some constant c < 1 and all sufficiently large n, then $T(n) = \Theta(f(n))$.
- MergeSort: $T(n) = 2T(n/2) + \theta(n)$
- a=2, b=2, f(n) = θ (n) watershed function: $n^{\log_b a} = n^{\log_2 2} = n^1 = n$
 - Does Case 2 hold?

Yes! for
$$k = 0$$
, $f(n) = \Theta(n^{\log_b a} \log^0 n) = \Theta(n)$

• So the solution is $T(n) = \Theta(n^{\log_b a} \log^{k+1} n) = \Theta(n \log n)$

> The Master Theorem: Further examples (1)

- 1. If there exists a constant $\epsilon > 0$ such that $f(n) = O(n^{\log_b a \epsilon})$, then $T(n) = \Theta(n^{\log_b a})$.
- 2. If there exists a constant $k \ge 0$ such that $f(n) = \Theta(n^{\log_b a} \lg^k n)$, then $T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$.
- 3. If there exists a constant $\epsilon > 0$ such that $f(n) = \Omega(n^{\log_b a + \epsilon})$, and if f(n) additionally satisfies the *regularity condition* $af(n/b) \le cf(n)$ for some constant c < 1 and all sufficiently large n, then $T(n) = \Theta(f(n))$.
- T(n) = 9T(n/3) + n
- a=9, b=3, f(n) = n watershed function: $n^{\log_b a} = n^{\log_3 9} = n^2$
- Does Case 1 hold? Does the watershed function must grow polynomially faster than f(n)?

Yes!
$$f(n) = n = O(n^{\log_b a - \epsilon}) = O(n^{2 - \epsilon})$$
 for any $\epsilon < 1$

• So the solution is $T(n) = \theta(n^{\log_b a}) = \theta(n^2)$ CSE217: Data Structures & Algorithm Analysis

> The Master Theorem: Further examples (2)

- 1. If there exists a constant $\epsilon > 0$ such that $f(n) = O(n^{\log_b a \epsilon})$, then $T(n) = \Theta(n^{\log_b a})$.
- 2. If there exists a constant $k \ge 0$ such that $f(n) = \Theta(n^{\log_b a} \lg^k n)$, then $T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$.
- 3. If there exists a constant $\epsilon > 0$ such that $f(n) = \Omega(n^{\log_b a + \epsilon})$, and if f(n) additionally satisfies the *regularity condition* $af(n/b) \le cf(n)$ for some constant c < 1 and all sufficiently large n, then $T(n) = \Theta(f(n))$.
- $T(n) = 3T(n/4) + n \log n$
- a=3, b=4, f(n) = n log n, watershed function: $n^{\log_b a} = n^{\log_4 3} = n^{0.793}$
- Does Case 1 hold? Does the watershed function must grow polynomially faster than f(n)?

The Master Theorem: Further examples (2)

- 1. If there exists a constant $\epsilon > 0$ such that $f(n) = O(n^{\log_b a \epsilon})$, then $T(n) = \Theta(n^{\log_b a})$.
- 2. If there exists a constant $k \ge 0$ such that $f(n) = \Theta(n^{\log_b a} \lg^k n)$, then $T(n) = \Theta(n^{\log_b a} \lg^{k+1} n)$.
- 3. If there exists a constant $\epsilon > 0$ such that $f(n) = \Omega(n^{\log_b a + \epsilon})$, and if f(n) additionally satisfies the *regularity condition* $af(n/b) \le cf(n)$ for some constant c < 1 and all sufficiently large n, then $T(n) = \Theta(f(n))$.
- $T(n) = 3T(n/4) + n \log n$
- a=3, b=4, f(n) = n log n, watershed function: $n^{\log_b a} = n^{\log_4 3} = n^{0.793}$
- Does Case 3 hold? Does the watershed function must grow polynomially slower than f(n)?

Yes!
$$f(n) = n \log n = \Omega(n^{\log_b a + \epsilon}) = \Omega(n^{0.793 + \epsilon})$$
 for any $0 < \epsilon$
 < 0.207 and $af\left(\frac{n}{b}\right) = 3\left(\frac{n}{4}\right)(\log n/4) \le c \ n \log n$ for $c = 3/4$

• So the solution is $T(n) = \theta(f(n)) = \theta(n \log n)$ CSE217: Data Structures & Algorithm Analysis

Summary

- The divide-and-conquer design paradigm
 - Divides a problem into smaller subproblems of the same kind
 - Solves these subproblems recursively, and then
 - Combines these solutions to an overall solution.
- MergeSort uses divide-and-conquer to sort in time $\Theta(n \log n)$ (best case = worst case).
- It's possible to sort n elements in worst-case time $\Theta(n \log n)$!
- Drawback: MergeSort does not sort in place.
 - "In place": sorting using only O(1) additional space.
- The runtime of recursive algorithms can be analysed by solving a recurrence equation.