

Algorithmns and Datastructures

Divide and Conquer, Master theorem

Albert-Ludwigs-Universität Freiburg



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Algorithmns and Datastructures, March 2016

Divide and Conquer

- Concept

- Maximum Subtotal

Recursion Equations

- Substitution Method

- Recursion Tree Method

- Master theorem

 - Master theorem (Simple Form)

 - Master theorem (General Form)

Divide and Conquer

Concept

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Divide and Conquer

Introduction



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Concept:

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- **Recursive** application of the algorithm on smaller subproblems

Concept:

- **Divide** the problem into smaller subproblems
- **Conquer** the subproblems through recursive solving.
If subproblems are small enough solve them directly
- **Connect** all subsolutions to solve the overall problem

- **Recursive** application of the algorithm on smaller subproblems
- **Direct** solving of small subproblems

Divide and Conquer

Concept

Maximum Subtotal

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Divide and Conquer

Maximum Subtotal



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- Progression X of n integers

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Output:

- Maximum sum of an uninterrupted subsequence of X and its index boundary

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Output:

- Maximum sum of an uninterrupted subsequence of X and its index boundary

Table: Input values

Index	0	1	2	3	4	5	6	7	8	9
Value	31	-41	59	26	-53	58	97	-93	-23	84

Output: Sum: 187, Start: 2, End: 6

Idea:



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- Solve the left / right half of the problem **recursive**

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- Combine both solutions into a overall solution
- The maximum is located in the **left half (A)** or the **right half (B)**
- The maximum interval can **overlap with the border (C)**

Principle:



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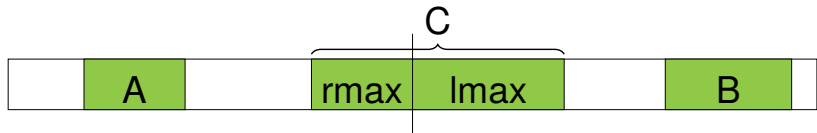
- Small problems are solved directly: $n = 1 \Rightarrow \text{max} = X[0]$

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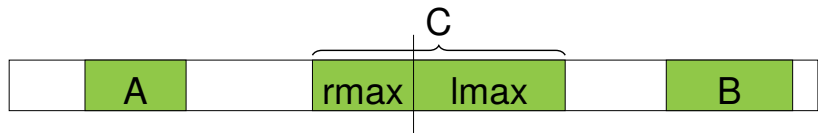
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- To solve *C* we have to calculate *rmax* and *lmax*

Principle:



- Small problems are solved directly: $n = 1 \Rightarrow \text{max} = X[0]$
- Big problems are decomposed into two subproblems and solved recursively. Subsolutions A and B are returned.
- To solve C we have to calculate $rmax$ and $lmax$
- Overall solution is maximum of $A B C$

Divide and Conquer

Maximum Subtotal - Python



```
def maxSubArray(X, i, j):
```

Divide and Conquer

Maximum Subtotal - Python

```
def maxSubArray(X, i, j):  
    if i == j: # trivial case  
        return (X[i], i, i)  
    m = (i + j) / 2
```

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    m = (i + j) / 2  
    #Solutions for A and B  
    A = maxSubArray(X, i, m)  
    B = maxSubArray(X, m + 1, j)
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    B = maxSubArray(X, m + 1, j)  
    #rmax and lmax for bordercase C  
    C1 = rmax(X, i, m)  
    C2 = lmax(X, m + 1, j)  
    C = (C1[0] + C2[0], C1[1], C2[1])
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    C = (C1[0] + C2[0], C1[1], C2[1])  
    #Solution is maximum of A,B,C  
    return max([A, B, C], \  
        key=lambda item: item[0])
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def maxSubArray(X, i, j):  
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    A = maxSubArray(X, i, m)  
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    C = (C1[0] + C2[0], C1[1], C2[1])  
    #Solution is maximum of A,B,C  
    return max([A, B, C], \  
        key=lambda item: item[0])  
    #Simplification: only maximum
```

Divide and Conquer

Maximum Subtotal - Python

```
#Alternative trivial case  
def maxSubArray(X, i, j):
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def maxSubArray(X, i, j):
    # trivial: only one element
    if i == j:
        return (X[i], i, i)
```



```
#Alternative trivial case
def maxSubArray(X, i, j):
    # trivial: only one element
    if i == j:
        return (X[i], i, i)
    # trivial: only two elements
    if i + 1 == j:
        return max([
            (X[i], i, i),
            (X[j], j, j),
            (X[i] + X[j], i, j)
        ], key=lambda item: item[0])
    ... # continue as before
```

Divide and Conquer

Maximum Subtotal - Python



```
#Implementation max  
def max(a, b, c):
```

Divide and Conquer

Maximum Subtotal - Python

```
#Implementation max
def max(a, b, c):
    if a > b:
        if a > c:
            return a
        else:
            return c
```

```
#Implementation max
def max(a, b, c):
    if a > b:
        if a > c:
            return a
        else:
            return c
    else:
        if c > b:
            return c
        else:
            return b
```

Divide and Conquer

Maximum Subtotal - Python



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#Alternative implementation max
```

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```
def max(a, b):  
    if a > b:  
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    else:  
        return b
```

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```
def max(a, b):  
    if a > b:  
        return a  
    else:  
        return b  
  
def maxTripel(a, b, c):  
    return max(max(a,b),c)
```

```
#Implementation left maximum
def lmax(X, i, j):
    maxSum = (X[i], i)
    s = X[i]

    # sum up from the lower index going up
    # (from left to right)
    for k in range(i+1, j+1):
        s += X[k]

        if s > maxSum[0]:
            maxSum = (s, k)

    return maxSum
```



```
#Implementation right maximum
def rmax(X, i, j):
    maxSum = (X[j], j)
    s = X[i]

    # sum up from the upper index going down
    # (from right to left)
    for k in range(j-1, i-1, -1):
        s += X[k]

        if s > maxSum[0]:
            maxSum = (s, k)

    return maxSum
```

Table: *lmax* example

index	i	$i + 1$	\dots	\dots	$j - 1$	j
X	58	-53	26	59	-41	31
<i>sum</i>	58	5	31	90	49	80
<i>lmax</i>	58	58	58	90	90	90

Table: *lmax* example

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- The *sum* and *lmax* are initialized with $X[i]$

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- The *sum* and *lmax* are initialized with $X[i]$
- We iterate over X from $i + 1$ to j and update *sum*

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- The *sum* and *lmax* are initialized with $X[i]$
- We iterate over X from $i + 1$ to j and update *sum*
- If $s > lmax$ then *lmax* gets updated

Divide and Conquer

Maximum Subtotal



Call with array of four elements

`maxSubArray(-3,9,-4,7)`

in fact:

`maxSubArray(X,0,3)`
with `X=[-3,9,-4,7]`

Divide and Conquer

Maximum Subtotal



Call with array of four elements

$\text{maxSubArray}(-3, 9, -4, 7)$

in fact:

$\text{maxSubArray}(X, 0, 3)$
with $X = [-3, 9, -4, 7]$

Call with array of two elements

$\text{maxSubArray}(-3, 9)$

$\text{maxSubArray}(-4, 7)$

Divide and Conquer

Maximum Subtotal



Call with array of four elements

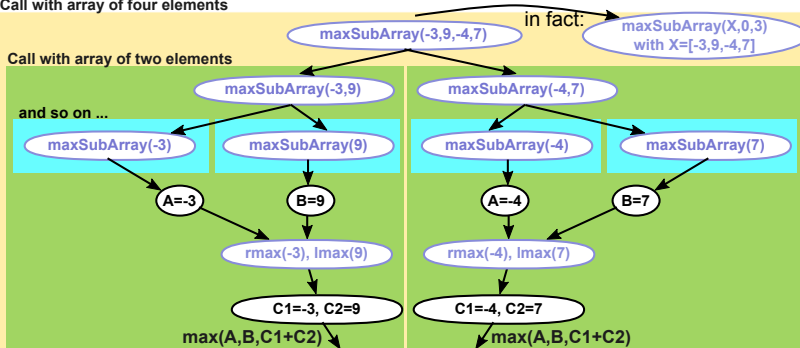


Divide and Conquer

Maximum Subtotal



Call with array of four elements



Divide and Conquer

Maximum Subtotal



Call with array of four elements

Call with array of two elements



```
def maxSubArray(X, i, j):  
    if i == j:  
        return (X[i], i, i)  
  
    m = (i + j) / 2  
    A = maxSubArray(X, i, m)  
    B = maxSubArray(X, m + 1, j)  
  
    C1 = rmax(X, i, m)  
    C2 = lmax(X, m + 1, j)  
    C = (C1[0] + C2[0], C1[1], C2[1])  
  
    return max([A, B, C], \  
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def maxSubArray(X, i, j):  
    if i == j:                                     # 0(1)  
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    m = (i + j) / 2                                # O(1)  
    A = maxSubArray(X, i, m)                       # T(n/2)  
    B = maxSubArray(X, m + 1, j)  
  
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    return max([A, B, C], \                   # O(1)  
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```

Recursion equation:

$$T(n) = \begin{cases} \Theta(1) & n = 1 \\ \underbrace{2 \cdot T\left(\frac{n}{2}\right)}_{\text{solving of subproblems}} + \underbrace{\Theta(n)}_{\text{cobination of solutions}} & n > 1 \end{cases}$$

$\underbrace{\Theta(1)}_{\text{trivial case}}$

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$\underbrace{\Theta(1)}_{\text{trivial case}}$

- There exist two constants a and b with:

$$T(n) \leq \begin{cases} a & n = 1 \\ 2 \cdot T\left(\frac{n}{2}\right) + b \cdot n & n > 1 \end{cases}$$

Recursion equation:

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- There exist two constants a and b with:

$$T(n) \leq \begin{cases} a & n = 1 \\ 2 \cdot T\left(\frac{n}{2}\right) + b \cdot n & n > 1 \end{cases}$$

- We define $c := \max(a, b)$:

$$T(n) \leq \begin{cases} c & n = 1 \\ 2 \cdot T\left(\frac{n}{2}\right) + c \cdot n & n > 1 \end{cases}$$

Divide and Conquer

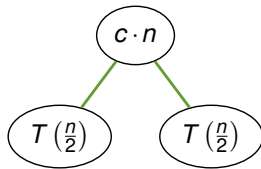
Maximum Subtotal - Illustration of $T(n)$



Figure: Illustration of the runtime

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$



$$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + c \cdot n$$

Figure: Illustration of the runtime

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$



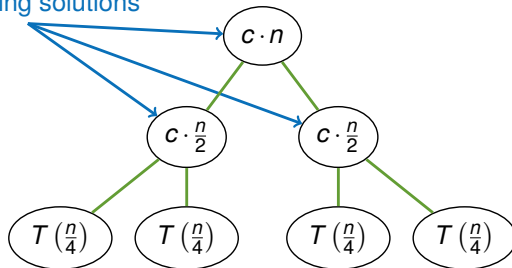
$$T\left(\frac{n}{2}\right) = 2 \cdot T\left(\frac{n}{4}\right) + c \cdot \frac{n}{2}$$

Figure: Illustration of the runtime

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$

combining solutions



$$T\left(\frac{n}{2}\right) = 2 \cdot T\left(\frac{n}{4}\right) + c \cdot \frac{n}{2}$$

Figure: Illustration of the runtime

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$



Figure: Illustration of the runtime

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$

$$c \cdot n$$

1 node processing n elements
 $\Rightarrow c \cdot n$

Figure: Recursion tree method

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$



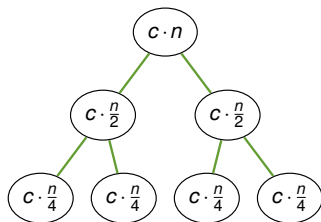
1 node processing n elements
 $\Rightarrow c \cdot n$

2 nodes processing $\frac{n}{2}$ elements
 $\Rightarrow 2c \cdot \frac{n}{2} = c \cdot n$

Figure: Recursion tree method

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$



1 node processing n elements
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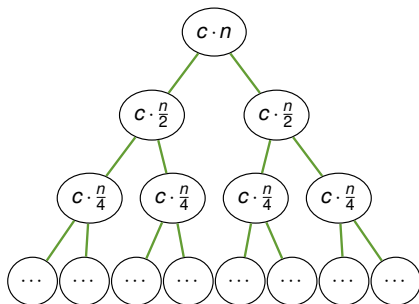
2 nodes processing $\frac{n}{2}$ elements
 $\Rightarrow 2c \cdot \frac{n}{2} = c \cdot n$

4 nodes processing $\frac{n}{4}$ elements
 $\Rightarrow 4c \cdot \frac{n}{4} = c \cdot n$

Figure: Recursion tree method

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$



1 node processing n elements
 $\Rightarrow c \cdot n$

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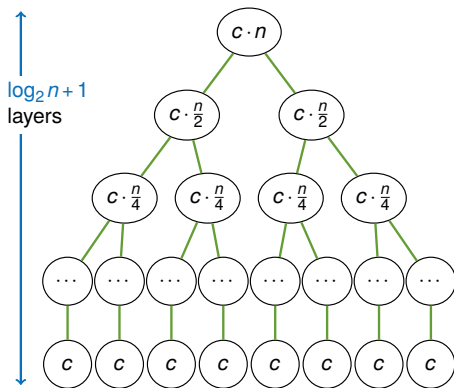
4 nodes processing $\frac{n}{4}$ elements
 $\Rightarrow 4c \cdot \frac{n}{4} = c \cdot n$

2^j nodes processing $\frac{n}{2^j}$ elements
 $\Rightarrow 2^j c \cdot \frac{n}{2^j} = c \cdot n$

Figure: Recursion tree method

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$



1 node processing n elements
 $\Rightarrow c \cdot n$

2 nodes processing $\frac{n}{2}$ elements
 $\Rightarrow 2c \cdot \frac{n}{2} = c \cdot n$

4 nodes processing $\frac{n}{4}$ elements
 $\Rightarrow 4c \cdot \frac{n}{4} = c \cdot n$

2^i nodes processing $\frac{n}{2^i}$ elements
 $\Rightarrow 2^i c \cdot \frac{n}{2^i} = c \cdot n$

n nodes processing 1 element
 $\Rightarrow c \cdot n$

Figure: Recursion tree method

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$



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Depth:

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$



Depth:

- Top level with depth $i = 0$

Depth:

- Top level with depth $i = 0$
- Lowest level with $2^i = n$ elements

$$\Rightarrow i = \log_2 n$$

Divide and Conquer

Maximum Subtotal - Illustration of $T(n)$

Depth:

- Top level with depth $i = 0$
- Lowest level with $2^i = n$ elements

$$\Rightarrow i = \log_2 n$$

Runtime:

Depth:

- Top level with depth $i = 0$
- Lowest level with $2^i = n$ elements

$$\Rightarrow i = \log_2 n$$

Runtime:

- A total of $\log_2 n + 1$ levels with each cost of $c \cdot n$
The costs of merging the solutions and solving of the trivial problems are the same here

Depth:

- Top level with depth $i = 0$
- Lowest level with $2^i = n$ elements

$$\Rightarrow i = \log_2 n$$

Runtime:

- A total of $\log_2 n + 1$ levels with each cost of $c \cdot n$

The costs of merging the solutions and solving of the trivial problems are the same here

$$T(n) = c \cdot n \log_2 n + c \cdot n \in \Theta(n \log n)$$

Divide and Conquer

Maximum Subtotal - Summary



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- There is an approach running in $O(n)$ if you assume that all subtotals are positive

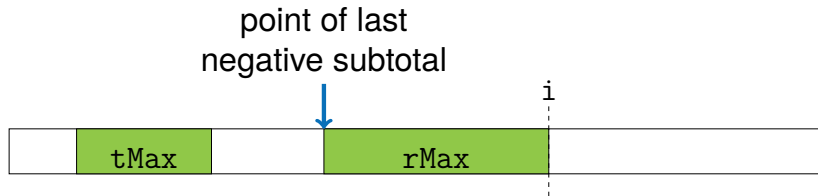


Figure: Scanning the array in linear time

Divide and Conquer

Maximum Subtotal - Python



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#Implementation - linear runtime  
def maxSubArray(X):
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        if rMax > tMax:  
            tMax, itMax = rMax, irMax  
  
    return (tMax, itMax)
```

Divide and Conquer

Concept

Maximum Subtotal

Recursion Equations

Substitution Method

Recursion Tree Method

Master theorem

Master theorem (Simple Form)

Master theorem (General Form)

Recursion equation:

- Describes the runtime for recursive functions:

$$T(n) = \begin{cases} \overbrace{f_0(n)}^{\text{trivial case for } n_0} & n = n_0 \\ \underbrace{a \cdot T\left(\frac{n}{b}\right)}_{\substack{\text{solving of } a \\ \text{subproblems} \\ \text{with reduced} \\ \text{input size } \frac{n}{b}}} + \underbrace{f(n)}_{\substack{\text{slicing and} \\ \text{splicing of} \\ \text{subsolutions}}} & n > n_0 \end{cases}$$



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- $T(n)$ is only defined for integers of $\frac{n}{b}$ which is often ignored in benefit of a simpler solution

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- Guess the solution and prove it with induction

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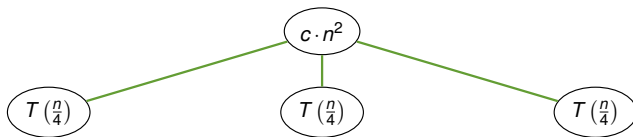
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Figure: Recursion tree of example

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Figure: Recursion tree of example

$$T(n) = 3 \cdot T\left(\frac{n}{4}\right) + c \cdot n^2$$



$$T(n) = 12 \cdot T\left(\frac{n}{16}\right) + 3c \cdot \left(\frac{n}{4}\right)^2 + c \cdot n^2$$

Figure: Recursion tree of example



Figure: Levels of the recursion tree



Costs of connecting the partial solutions:
(excludes the last layer)

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uses $x^{a \cdot b} = (x^a)^b$

- This term will recur in the master theorem

Recursion Equations

Total costs



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$$T(n) = \underbrace{\sum_{i=0}^{(\log_4 n)-1} \left(\frac{3}{16}\right)^i \cdot c \cdot n^2}_{\substack{\text{geometric series,} \\ \text{constant} \\ \text{even with} \\ \text{infinite elements}}} + \underbrace{d \cdot n^{\log_4 3}}_{\substack{\log_4 3 < 1, \\ \text{grows a lot} \\ \text{slower than } n^2}} \in O(n^2)$$

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- Here: The costs of connecting the partial problems dominate

Recursion Equations

Geometric Series



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- Therefore constant

Recursion Equations

Proof of $O(n^2)$



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■ We know:

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- Presumption: $T(n) \in O(n^2)$, so there exists a $k > 0$ with

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Recursion Equations

Proof of $O(n^2)$



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$$T(n) < k \cdot n^2$$

- Substitution method:

$$\begin{aligned} T(n) &\leq 3 \cdot T\left(\frac{n}{4}\right) + c \cdot n^2 \\ &\leq 3k \cdot \left(\frac{n}{4}\right)^2 + c \cdot n^2 \\ &= \frac{3}{16}k \cdot n^2 + c \cdot n^2 \\ &\leq k \cdot n^2 \qquad \text{for } k \geq \frac{16}{13}c \end{aligned}$$

Divide and Conquer

Concept

Maximum Subtotal

Recursion Equations

Substitution Method

Recursion Tree Method

Master theorem

Master theorem (Simple Form)

Master theorem (General Form)



Master theorem:

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- Approach to solve for a recursion equation of the form:

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 - ... which takes **$f(n)$** steps to merge all partial solutions



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- **Simple form:** Special case with runtime of connecting the solutions $f(n) \in O(n)$

Recursion Equations

Master theorem (Simple Form)



Simple form:

Simple form:

$$T(n) = a \cdot T\left(\frac{n}{b}\right) + \underbrace{c \cdot n}_{\text{was any } f(n)}, \quad a \geq 1, b > 1, c > 0$$

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- This yields a runtime of:

$$T(n) = \begin{cases} \overbrace{\Theta(n^{\log_b a})}^{\text{Number of leaves}} & \text{if } a > b \\ \Theta(n \log n) & \text{if } a = b \\ \Theta(n) & \text{if } a < b \end{cases}$$

Recursion Equations

Master theorem (Simple Form)

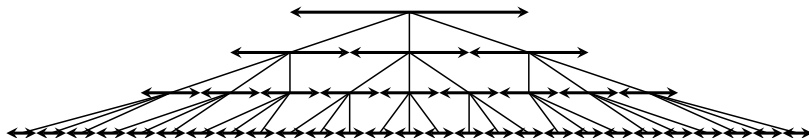


Figure: Simple recursion equation with $a = 3, b = 2$

Recursion Equations

Master theorem (Simple Form)

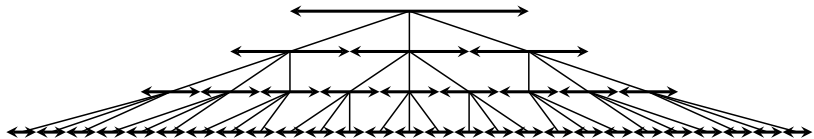


Figure: Simple recursion equation with $a = 3, b = 2$

Case 1: $a > b$

Recursion Equations

Master theorem (Simple Form)

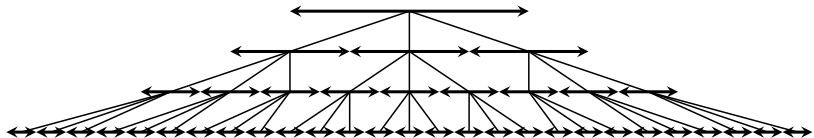


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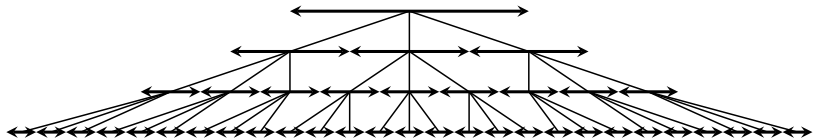


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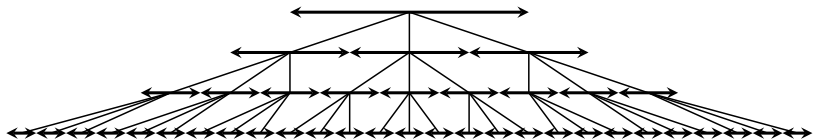


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Recursion Equations

Master theorem (Simple Form)

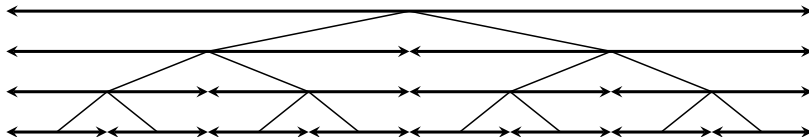


Figure: Simple recursion equation with $a = 2, b = 2$

Recursion Equations

Master theorem (Simple Form)



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Case 2: $a = b$

Recursion Equations

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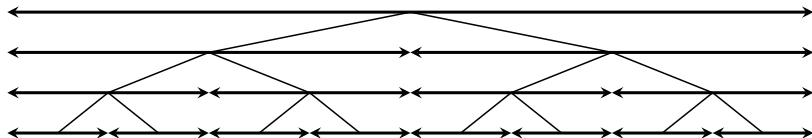


Figure: Simple recursion equation with $a = 2, b = 2$

Case 2: $a = b$

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Recursion Equations

Master theorem (Simple Form)



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- Each layer has equal costs, $\log n$ layers

Recursion Equations

Master theorem (Simple Form)

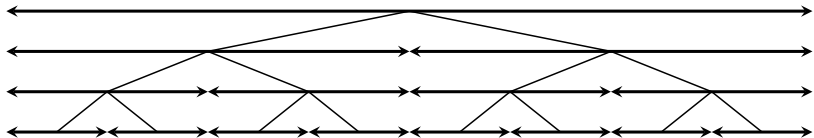


Figure: Simple recursion equation with $a = 2, b = 2$

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- Each layer has equal costs, $\log n$ layers
- Runtime of $\Theta(n \log n)$

Recursion Equations

Master theorem (Simple Form)



Figure: Simple recursion equation with $a = 2, b = 3$

Recursion Equations

Master theorem (Simple Form)

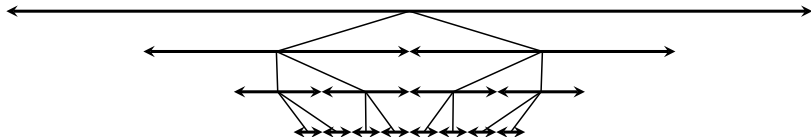


Figure: Simple recursion equation with $a = 2, b = 3$

Case 3: $a < b$

Recursion Equations

Master theorem (Simple Form)

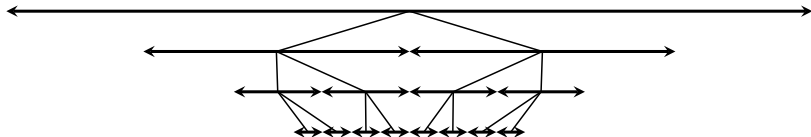


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Recursion Equations

Master theorem (Simple Form)



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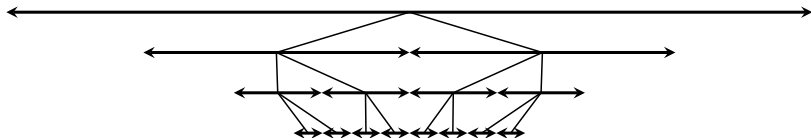


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- Runtime of $\Theta(n)$

For a recursion equation like

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- Proof with *geometric series*: Number of operations per layer grows / shrinks by constant factor $\frac{a}{b}$

Divide and Conquer

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Master theorem

Master theorem (Simple Form)

Master theorem (General Form)

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- **Case 1:** $T(n) \in \Theta(n^{\log_b a})$ if $f(n) \in \mathcal{O}(n^{\log_b a - \varepsilon})$, $\varepsilon > 0$

Solving the partial problems dominates
(last layer, leaves)

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- **Case 2:** $T(n) \in \Theta(n^{\log_b a} \log n)$ if $f(n) \in \Theta(n^{\log_b a})$

Each layer has equal costs, $\log_b n$ layers



Master theorem (general form):

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Connecting all partial solutions dominates
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Regularity condition:

$$a \cdot f\left(\frac{n}{b}\right) \leq c \cdot f(n), \quad 0 \leq c \leq 1, \\ n > n_0$$



Case 1 - Example:

if $f(n) \in O(n^{\log_b a - \varepsilon})$, $\varepsilon > 0$

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$$\blacksquare T(n) = 8 \cdot T\left(\frac{n}{2}\right) + 1000 \cdot n^2$$

$$a = 8, b = 2, f(n) = 1000 \cdot n^2, \underbrace{\log_b a = \log_2 8 = 3}_{n^3 \text{ leaves}}$$

$$f(n) \in \mathcal{O}(n^{3-\varepsilon}) \Rightarrow T(n) \in \Theta(n^3)$$

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■ $T(n) = 9 \cdot T\left(\frac{n}{3}\right) + 17 \cdot n$

$$a = 9, b = 3, f(n) = 17 \cdot n, \underbrace{\log_b a = \log_3 9 = 2}_{n^2 \text{ leaves}}$$

$$f(n) \in \mathcal{O}(n^{2-\varepsilon}) \Rightarrow T(n) \in \Theta(n^2)$$

Recursion Equations

Master theorem (General Form) - Case 2



Case 2: if $f(n) \in \Theta(n^{\log_b a})$

Each layer has equal costs, $\log n$ layers

Recursion Equations

Master theorem (General Form) - Case 2

Case 2: $T(n) \in \Theta(n^{\log_b a} \log n)$ if $f(n) \in \Theta(n^{\log_b a})$

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■ $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 10 \cdot n$

$$a = 2, b = 2, f(n) = 10 \cdot n, \underbrace{\log_b a = \log_2 2 = 1}_{n^1 \text{ leaves}}$$

$$f(n) \in \Theta(n^{\log_2 2}) \Rightarrow T(n) \in \Theta(n \log n)$$

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■ $T(n) = T\left(\frac{2n}{3}\right) + 1$

$$a = 1, b = \frac{2}{3}, f(n) = 1, \underbrace{\log_b a = \log_{3/2} 1 = 0}_{n^0 \text{ leaves} = 1 \text{ leaf}}$$

$$f(n) \in \Theta(n^{\log_{3/2} 1}) \Rightarrow T(n) \in \Theta(n^0 \log n) = \Theta(\log n)$$



Case 3:

if $f(n) \in \Omega(n^{\log_b a + \varepsilon})$, $\varepsilon > 0$

Connecting all partial solutions dominates (first layer, root)



Case 3: $T(n) \in \Theta(f(n))$ if $f(n) \in \Omega(n^{\log_b a + \varepsilon})$, $\varepsilon > 0$

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$$a = 2, b = 2, f(n) = n^2, \underbrace{\log_b a = \log_2 2 = 1}_{n^1 \text{ leaves}}$$

$$f(n) \in \Omega(n^{1+\varepsilon})$$

Check if **regularity condition** also holds:

$$2 \cdot \left(\frac{n}{2}\right)^2 \leq c \cdot n^2 \quad \Rightarrow \quad \frac{1}{2} \cdot n^2 \leq c \cdot n^2 \quad \Rightarrow \quad c \geq \frac{1}{2}$$

$$\Rightarrow T(n) \in \Theta(n^2)$$



Master theorem:



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$n \log n$ is *asymptotically* larger than n ,
but not *polynomial* larger



Master theorem:



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- Three cases depending on the dominance of the terms

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- **Case 3:** Connecting all partial solutions is *polynomial* bigger than solving all partial problems

$$T(n) \in \Theta(f(n))$$

■ General

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■ Master theorem

[Wik] [Master theorem](#)

https://en.wikipedia.org/wiki/Master_theorem