

# Algorithms and Datastructures

Divide and Conquer, Master theorem

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# Structure

## 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

## Introduction

**Concept:**

# Divide and Conquer

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- ▶ **Divide** the problem into smaller subproblems

# Divide and Conquer

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### Concept:

- ▶ **Divide** the problem into smaller subproblems
- ▶ **Conquer** the subproblems through recursive solving.  
If subproblems are small enough solve them directly

# Divide and Conquer

## Introduction

### 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

# Divide and Conquer

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If subproblems are small enough solve them directly
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- ▶ **Recursive** application of the algorithm on smaller subproblems

# Divide and Conquer

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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



# Structure

## 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

Maximum Subtotal

**Input:**

**Output:**

# Divide and Conquer

## Maximum Subtotal

### Input:

- ▶ Sequence  $X$  of  $n$  integers

### Output:

# Divide and Conquer

## Maximum Subtotal

### Input:

- ▶ Sequence  $X$  of  $n$  integers

### Output:

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

# Divide and Conquer

## Maximum Subtotal

### Input:

- ▶ Sequence  $X$  of  $n$  integers

### 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

# Divide and Conquer

## Maximum Subtotal

**Idea:**



# Divide and Conquer

## Maximum Subtotal

**Idea:**



- Solve the left / right half of the problem [recursive](#)

# Divide and Conquer

## Maximum Subtotal

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- ▶ Solve the left / right half of the problem [recursive](#)
- ▶ Combine both solutions into a overall solution



# Divide and Conquer

## Maximum Subtotal

### Idea:



- ▶ Solve the left / right half of the problem **recursive**
- ▶ Combine both solutions into a overall solution
- ▶ The maximum is located in the **left half (A)** or the **right half (B)**

# Divide and Conquer

## Maximum Subtotal

### Idea:



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

# Divide and Conquer

## Maximum Subtotal

### Principle:



# Divide and Conquer

## Maximum Subtotal

### Principle:

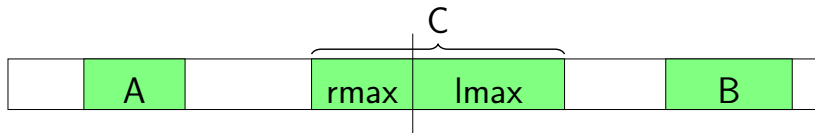


- ▶ Small problems are solved directly:  $n = 1 \Rightarrow \max = X[0]$

# Divide and Conquer

## Maximum Subtotal

### 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

# Divide and Conquer

## Maximum Subtotal

### Principle:



- ▶ Small problems are solved directly:  $n = 1 \Rightarrow \text{max} = X[0]$
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- ▶ To solve  $C$  we have to calculate  $\text{rmax}$  and  $\text{lmax}$

# Divide and Conquer

## Maximum Subtotal

### 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  $\text{rmax}$  and  $\text{lmax}$
- ▶ Overall solution is maximum of  $A$ ,  $B$  and  $C$

# 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)  
  
    # recursive subsolutions for A, B  
    m = (i + j) / 2
```

# Divide and Conquer

## Maximum Subtotal - Python

```
def maxSubArray(X, i, j):  
    if i == j: # trivial case  
        return (X[i], i, i)  
  
    # recursive subsolutions for A, B  
    m = (i + j) / 2  
    A = maxSubArray(X, i, m)  
    B = maxSubArray(X, m + 1, j)
```

# Divide and Conquer

## Maximum Subtotal - Python

```
def maxSubArray(X, i, j):  
    if i == j: # trivial case  
        return (X[i], i, i)  
  
    # recursive subsolutions for A, B  
    m = (i + j) / 2  
    A = maxSubArray(X, i, m)  
    B = maxSubArray(X, m + 1, j)  
  
    # rmax and lmax for corner case C  
    C1, C2 = rmax(X, i, m), lmax(X, m + 1, j)  
    C = (C1[0] + C2[0], C1[1], C2[1])
```

# Divide and Conquer

## Maximum Subtotal - Python

```
def maxSubArray(X, i, j):  
    if i == j: # trivial case  
        return (X[i], i, i)  
  
    # recursive subsolutions for A, B  
    m = (i + j) / 2  
    A = maxSubArray(X, i, m)  
    B = maxSubArray(X, m + 1, j)  
  
    # rmax and lmax for corner case C  
    C1, C2 = rmax(X, i, m), lmax(X, m + 1, j)  
    C = (C1[0] + C2[0], C1[1], C2[1])  
  
    # compute solution from results A, B, C  
    return max([A, B, C], key=lambda i: i[0])
```

# Divide and Conquer

## Maximum Subtotal - Python

```
#Alternative trivial case  
def maxSubArray(X, i, j):
```

# Divide and Conquer

## Maximum Subtotal - Python

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

# Divide and Conquer

## Maximum Subtotal - Python

```
#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
```

# Divide and Conquer

## Maximum Subtotal - Python

```
#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

```
#Alternative implementation max
```

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## Maximum Subtotal - Python

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

# Divide and Conquer

## Maximum Subtotal - Python

```
#Alternative implementation max
```

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

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

# Divide and Conquer

## Maximum Subtotal - Python

```
#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
```

# Divide and Conquer

## Maximum Subtotal - Python

```
#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
```

# Divide and Conquer

## Maximum Subtotal

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



# Divide and Conquer

## Maximum Subtotal

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

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

# Divide and Conquer

## Maximum Subtotal

Table:  $lmax$  example

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

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

# Divide and Conquer

## Maximum Subtotal

Table:  $lmax$  example

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

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

# Divide and Conquer

## Maximum Subtotal

Call with array of four elements

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

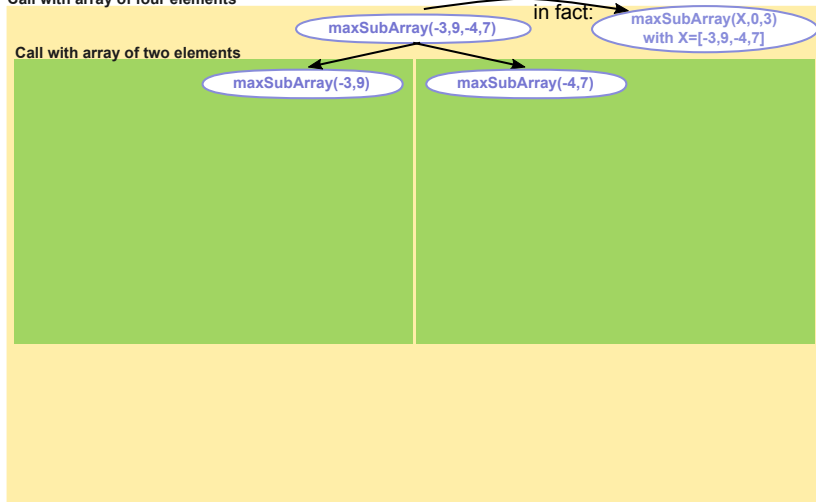
in fact:

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

# Divide and Conquer

## Maximum Subtotal

Call with array of four elements



# Divide and Conquer

## Maximum Subtotal

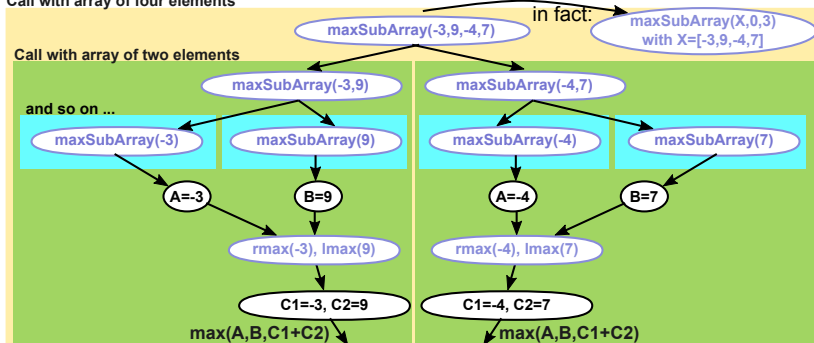
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# Divide and Conquer

## Maximum Subtotal

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# Divide and Conquer

## Maximum Subtotal - Python

```
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], \  
               key=lambda item: item[0])
```

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```
def maxSubArray(X, i, j):  
    if i == j:  
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# Divide and Conquer

## Maximum Subtotal - Python

```
def maxSubArray(X, i, j):  
    if i == j:                                     # O(1)  
        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)  
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    A = maxSubArray(X, i, m)  
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    m = (i + j) / 2                                # O(1)  
    A = maxSubArray(X, i, m)                       # T(n/2)  
    B = maxSubArray(X, m + 1, j)  
  
    C1 = rmax(X, i, m)  
    C2 = lmax(X, m + 1, j)  
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    A = maxSubArray(X, i, m)                        # T(n/2)  
    B = maxSubArray(X, m + 1, j)                    # T(n/2)  
  
    C1 = rmax(X, i, m)  
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    C1 = rmax(X, i, m)                             # O(n)  
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    B = maxSubArray(X, m + 1, j)                   # T(n/2)  
  
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## Maximum Subtotal - Python

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

# Divide and Conquer

Maximum Subtotal - Number of steps  $T(n)$

**Recursion equation:**

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

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

# Divide and Conquer

Maximum Subtotal - Number of steps  $T(n)$

**Recursion equation:**

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

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

- There exist two constants  $a$  and  $b$  with:

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

# Divide and Conquer

Maximum Subtotal - Number of steps  $T(n)$

**Recursion equation:**

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

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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  $T(n)$



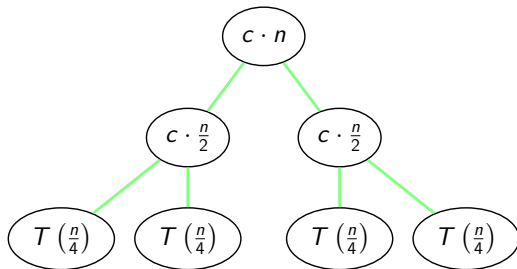
$$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + c \cdot n$$

Figure: Illustration of the runtime



# Divide and Conquer

Maximum Subtotal - Illustration of  $T(n)$

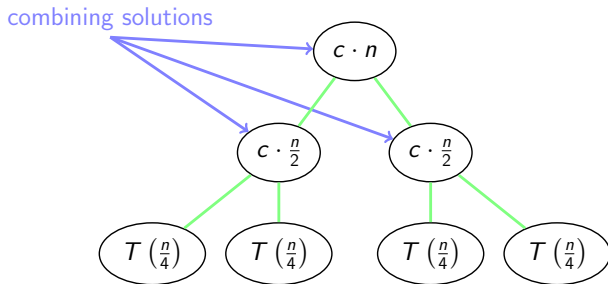


$$T\left(\frac{n}{2}\right) = 2 \cdot T\left(\frac{n}{4}\right) + c \cdot \frac{n}{2}$$

Figure: Illustration of the runtime

# Divide and Conquer

Maximum Subtotal - Illustration of  $T(n)$



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

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

$$\Rightarrow 2 c \cdot \frac{n}{2} = c \cdot n$$

Figure: Recursion tree method

# Divide and Conquer

Maximum Subtotal - Illustration of  $T(n)$



1 node processing  $n$  elements

$$\Rightarrow c \cdot n$$

2 nodes processing  $\frac{n}{2}$  elements

$$\Rightarrow 2 c \cdot \frac{n}{2} = c \cdot n$$

4 nodes processing  $\frac{n}{4}$  elements

$$\Rightarrow 4 c \cdot \frac{n}{4} = c \cdot n$$

Figure: Recursion tree method

# Divide and Conquer

## Maximum Subtotal - Illustration of $T(n)$



1 node processing  $n$  elements

$$\Rightarrow c \cdot n$$

2 nodes processing  $\frac{n}{2}$  elements

$$\Rightarrow 2 c \cdot \frac{n}{2} = c \cdot n$$

4 nodes processing  $\frac{n}{4}$  elements

$$\Rightarrow 4 c \cdot \frac{n}{4} = c \cdot n$$

$2^i$  nodes processing  $\frac{n}{2^i}$  elements

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

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

$$\Rightarrow 2 c \cdot \frac{n}{2} = c \cdot n$$

4 nodes processing  $\frac{n}{4}$  elements

$$\Rightarrow 4 c \cdot \frac{n}{4} = c \cdot n$$

$2^i$  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  $T(n)$

**Depth:**

# Divide and Conquer

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## Depth:

- ▶ Top level with depth  $i = 0$

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$$\Rightarrow i = \log_2 n$$

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# Divide and Conquer

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- ▶ 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

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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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# Divide and Conquer

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### Summary:

- ▶ Direct solution is slow with  $\mathcal{O}(n^3)$



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- ▶ Better solution with incremental update of sum was  $\mathcal{O}(n^2)$
- ▶ Divide and conquer approach results in  $\mathcal{O}(n \log n)$
- ▶ There is an approach running in  $\mathcal{O}(n)$  if you assume that all subtotals are positive

# Divide and Conquer

## Maximum Subtotal



Figure: Scanning the array in linear time

# Divide and Conquer

## Maximum Subtotal - Python

```
#Implementation - linear runtime  
def maxSubArray(X):
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# Divide and Conquer

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# Divide and Conquer

## Maximum Subtotal - Python

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#Implementation - linear runtime
def maxSubArray(X):
    # sum, start index
    rMax, irMax = 0, 0 # current maximum
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    for i in range(len(X)):
        if rMax == 0:
            irMax = i
        rMax = max(0, rMax + X[i])
```

# Divide and Conquer

## Maximum Subtotal - Python

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#Implementation - linear runtime
def maxSubArray(X):
    # sum, start index
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    for i in range(len(X)):
        if rMax == 0:
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            rMax = max(0, rMax + X[i])

        if rMax > tMax:
            tMax, itMax = rMax, irMax

    return (tMax, itMax)
```



# Structure

## Divide and Conquer

- Concept

- Maximum Subtotal

## Recursion Equations

- Substitution Method

- Recursion Tree Method

- Master theorem

  - Master theorem (Simple Form)

  - Master theorem (General Form)

# Recursion Equations

## Recursion Equation

### Recursion equation:

- Describes the runtime for recursive functions:

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

# Recursion Equations

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- ▶ Normally  $a > 1$  and  $b > 1$
- ▶ Dependent on the strategy of solving  $T(n)$   $f_0$  is ignored
- ▶  $T(n)$  is only defined for integers of  $\frac{n}{b}$  which is often ignored in benefit of a simpler solution



# Structure

## Divide and Conquer

- Concept

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# Recursion Equations

## Substitution Method

**Substitution Method:**

# Recursion Equations

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- ▶ Guess the solution and prove it with induction

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

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- ▶ Guess the solution and prove it with induction
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$$T(n) = \begin{cases} 1 & n = 1 \\ 2 \cdot T\left(\frac{n}{2}\right) + n & n > 1 \end{cases}$$

- ▶ Assumption:  $T(n) = n + n \cdot \log_2 n$

# Recursion Equations

## Substitution Method

**Induction:**

# Recursion Equations

## Substitution Method

### **Induction:**

- ▶ Induction basis (for  $n = 1$ ):  $T(1) = 1 + 1 \cdot \log_2 1 = 1$

# Recursion Equations

## Substitution Method

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$$\begin{aligned} T(n) &= 2 \cdot T\left(\frac{n}{2}\right) + n \\ &\stackrel{IA}{=} 2 \cdot \left(\frac{n}{2} + \frac{n}{2} \cdot \log_2 \frac{n}{2}\right) + n \end{aligned}$$

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# Recursion Equations

## Substitution Method

**Substitution Method:**

# Recursion Equations

## Substitution Method

### **Substitution Method:**

- ▶ Alternative assumption

# Recursion Equations

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$$T(n) = \begin{cases} 1 & n = 1 \\ 2 \cdot T\left(\frac{n}{2}\right) + n & n > 0 \end{cases}$$



# Recursion Equations

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- ▶ Solution: Find  $c > 0$  with  $T(n) \leq c \cdot n \log_2 n$

# Recursion Equations

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# Structure

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# Recursion Equations

## Recursion Tree Method

**Recursion tree method:**

# Recursion Equations

## Recursion Tree Method

### **Recursion tree method:**

- ▶ Can be used to make assumptions about the runtime

# Recursion Equations

## Recursion Tree Method

### Recursion tree method:

- ▶ Can be used to make assumptions about the runtime
- ▶ Example:

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

# Recursion Equations

## Recursion Tree Method

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



Figure: Recursion tree of example

# Recursion Equations

## Recursion Tree Method

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# Recursion Equations

## Recursion Tree Method

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



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

Figure: Recursion tree of example

# Recursion Equations

## Recursion Tree Method



Figure: Levels of the recursion tree

# Recursion Equations

## Recursion Tree Method Costs

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

# Recursion Equations

## Recursion Tree Method Costs

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- ▶ Size of partial problems on level  $i$ :  $s_i(n) = \left(\frac{1}{4}\right)^i \cdot n$

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$$T_{i_p}(n) = c \cdot \left(\left(\frac{1}{4}\right)^i \cdot n\right)^2$$

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# Recursion Equations

## Recursion Tree Method Costs

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- ▶ Number of partial problems on level  $i$ :  $n_i = 3^i$
- ▶ Costs on level  $i$ :

$$T_i(n) = 3^i \cdot c \cdot \left(\left(\frac{1}{4}\right)^i \cdot n\right)^2 = \left(\frac{3}{16}\right)^i \cdot c \cdot n^2$$

# Recursion Equations

## Recursion Tree Method Costs

**Costs of solving partial solutions:** (only the last layer)



# Recursion Equations

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- ▶ Size of partial problems on the last level:  $s_{i+1}(n) = 1$

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# Recursion Equations

## Recursion Tree Method Costs

**Costs of solving partial solutions:** (only the last layer)

- ▶ Size of partial problems on the **last level**:  $s_{i+1}(n) = 1$
- ▶ Costs of partial problem on the **last level**:  $T_{i+1_p}(n) = d$
- ▶ With this the depth of the tree is:

$$\left(\frac{1}{4}\right)^i \cdot n = 1 \quad \Rightarrow \quad n = 4^i \quad \Rightarrow \quad i = \log_4 n$$

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- ▶ Number of partial problems on the last level:

$$n_{i+1} = 3^{\log_4 n}$$

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$$n_{i+1} = 3^{\log_4 n} = n^{\log_4 3} \quad \leftarrow \text{next slide}$$

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$$n_{i+1} = 3^{\log_4 n} = n^{\log_4 3} \quad \leftarrow \text{next slide}$$

- ▶ Costs on the last level:  $T_{i+1}(n) = d \cdot n^{\log_4 3}$

# Fun with logarithm

## Logarithm

- ▶ Transforming  $3^{\log_4 n}$  uses general log rules

$$\log_4 n = \log_4 \left( 3^{\log_3 n} \right) \quad \text{uses } n = 3^{\log_3 n}$$

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- ▶ This proves the general log rule  $\log_b c = \log_a c \cdot \log_b a$

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- ▶ Now the whole expression:

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uses reformulation above

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

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$$\text{uses } n = 3^{\log_3 n}$$

$$\text{uses } \log a^b = b \cdot \log a$$

- ▶ This proves the general log rule  $\log_b c = \log_a c \cdot \log_b a$
- ▶ Now the whole expression:

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uses reformulation above

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

# Fun with logarithm

## Logarithm

- ▶ Transforming  $3^{\log_4 n}$  uses general log rules

$$\begin{aligned}\log_4 n &= \log_4 \left( 3^{\log_3 n} \right) \\ &= \log_3 n \cdot \log_4 3\end{aligned}$$

$$\text{uses } n = 3^{\log_3 n}$$

$$\text{uses } \log a^b = b \cdot \log a$$

- ▶ This proves the general log rule  $\log_b c = \log_a c \cdot \log_b a$
- ▶ Now the whole expression:

$$\begin{aligned}3^{\log_4 n} &= 3^{\log_3 n \cdot \log_4 3} \\ &= \left( 3^{\log_3 n} \right)^{\log_4 3} \\ &= n^{\log_4 3}\end{aligned}$$

uses reformulation above

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

- ▶ This term will recur in the master theorem

# Recursion Equations

Total costs

**Total costs:**

# Recursion Equations

## Total costs

### Total costs:

- ▶ Costs of level  $i$ :  $T_i(n) = \left(\frac{3}{16}\right)^i \cdot c \cdot n^2$

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

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- ▶ Here: The costs of connecting the partial problems dominate

# Recursion Equations

## Geometric Series

- ▶ **Geometric progression:**

Quotient of two neighboring sequence parts is constant

$$2^0, 2^1, 2^2, \dots, 2^k$$

# Recursion Equations

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The series (cumulative sum) of a geometric sequence

- ▶ For  $|q| < 1$ :

$$\sum_{k=0}^{\infty} a_0 \cdot q^k = \frac{a_0}{1 - q} \Rightarrow \text{constant}$$

# Recursion Equations

Proof of  $O(n^2)$

**Proof of  $O(n^2)$ :**

# Recursion Equations

Proof of  $O(n^2)$

**Proof of  $O(n^2)$ :**

► We know:

$$\begin{aligned} T(n) &= 3T\left(\frac{n}{4}\right) + \Theta(n^2) \\ &\leq 3T\left(\frac{n}{4}\right) + c \cdot n^2 \end{aligned}$$

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# Structure

## Divide and Conquer

- Concept

- Maximum Subtotal

## Recursion Equations

- Substitution Method

- Recursion Tree Method

- Master theorem**

  - Master theorem (Simple Form)

  - Master theorem (General Form)



# Recursion Equations

## Master theorem

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# Recursion Equations

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

$$T(n) = a \cdot T\left(\frac{n}{b}\right) + f(n), \quad a \geq 1, b > 1$$

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

# Recursion Equations

## Master theorem (Simple Form)

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- ▶ In the examples we have seen that ...



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  - ▶ Or the runtime of **solving the problems** dominates
  - ▶ Or both have **equal influence on runtime**
- ▶ **Simple form:** Special case with runtime of connecting the solutions  $f(n) \in O(n)$

# Recursion Equations

Master theorem (Simple Form)

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# Recursion Equations

## Master theorem (Simple Form)

**Simple form:**

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

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- This yields a runtime of:

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



# Recursion Equations

## Master theorem (Simple Form)

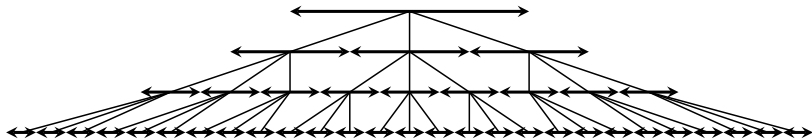


Figure: Simple recursion equation with  $a = 3, b = 2$

# Recursion Equations

## Master theorem (Simple Form)



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**Case 1:**  $a > b$

# Recursion Equations

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### Case 1: $a > b$

- ▶ Three partial problems with  $\frac{1}{2}$  the size

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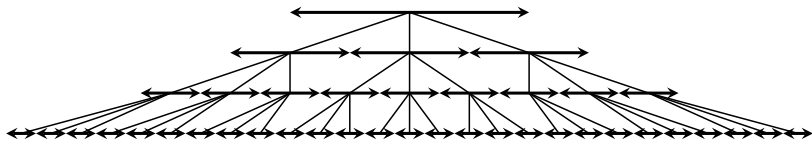


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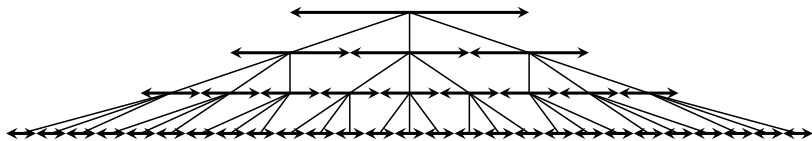


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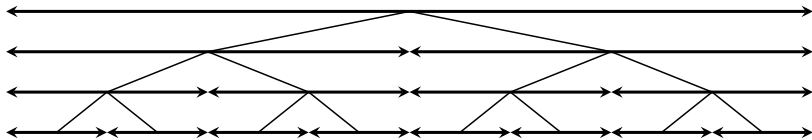


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# Recursion Equations

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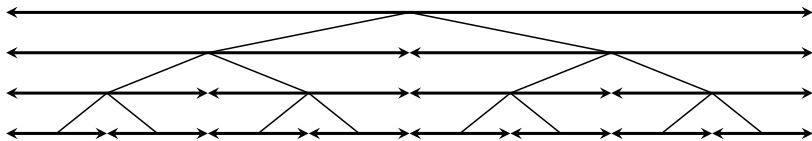


Figure: Simple recursion equation with  $a = 2, b = 2$

**Case 2:**  $a = b$

# Recursion Equations

## Master theorem (Simple Form)



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

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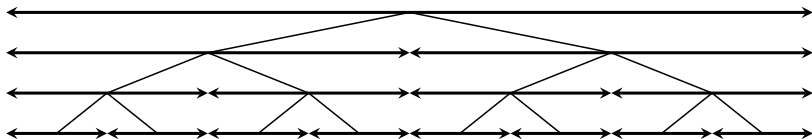


Figure: Simple recursion equation with  $a = 2, b = 2$

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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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# Recursion Equations

## Master theorem (Simple Form)



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

# Recursion Equations

## Master theorem (Simple Form)



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**Case 3:**  $a < b$

# Recursion Equations

## Master theorem (Simple Form)

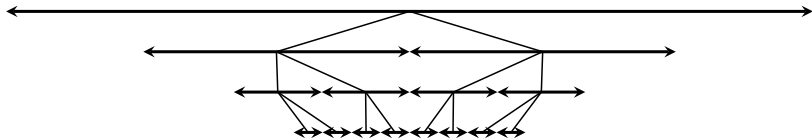


Figure: Simple recursion equation with  $a = 2, b = 3$

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# Recursion Equations

## Master theorem (Simple Form)



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

### Case 3: $a < b$

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- ▶ Connecting all partial solutions dominates (first layer, root)

# Recursion Equations

## Master theorem (Simple Form)



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

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# Recursion Equations

## Master theorem (Simple Form)

**For a recursion equation like**

$$T(n) = a \cdot T\left(\frac{n}{b}\right) + c \cdot n, \quad a \geq 1, b > 1, c > 0$$



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

# Structure

## Divide and Conquer

- Concept

- Maximum Subtotal

## Recursion Equations

- Substitution Method

- Recursion Tree Method

- Master theorem**

  - Master theorem (Simple Form)

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# Recursion Equations

## Master theorem (General Form)

**Master theorem (general form):**

# Recursion Equations

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# Recursion Equations

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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



# Recursion Equations

## Master theorem (General Form)

### Master theorem (general form):

- **Case 3:**  $T(n) \in \Theta(f(n))$  if  $f(n) \in \Omega(n^{\log_b a + \varepsilon})$ ,  $\varepsilon > 0$   
Connecting all partial solutions in first layer (root) dominates

Regularity condition:

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

# Recursion Equations

## Master theorem (General Form) - Case 1

### Case 1 - Example:

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

Solving the partial problems dominates (last layer, leaves)

if

# Recursion Equations

## Master theorem (General Form) - Case 1

**Case 1 - Example:**  $T(n) \in \Theta(n^{\log_b a})$

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

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

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

# Recursion Equations

## Master theorem (General Form) - Case 1

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

Solving the partial problems dominates (last layer, leaves)

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

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

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

# 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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# Recursion Equations

## Master theorem (General Form) - Case 2

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

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

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

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

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



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

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

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

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

# Recursion Equations

## Master theorem (General Form) - Case 3

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

Connecting all partial solutions in first layer (root) dominates

# Recursion Equations

## Master theorem (General Form) - Case 3

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

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

# Recursion Equations

## Master theorem (General Form) - Case 3

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- ▶  $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + n^2$
- ▶  $f(n) \in \Omega(n^{1+\varepsilon})$
- ▶ Check if **regularity condition** also holds:

$$a \cdot f\left(\frac{n}{b}\right) \leq c \cdot f(n)$$

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

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



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

# Recursion Equations

## Master theorem - Summary

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- ▶ **Case 2:** Each layer has equal costs

$$T(n) \in \Theta(n^{\log_b a} \log n), \quad \log n \text{ layers}$$

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- ▶ Three cases depending on the dominance of the terms
- ▶ **Case 1:** Solving the partial problems is *polynomial* bigger than merging all solutions  
 $T(n) \in \Theta(n^{\log_b a})$ ,  $T(n) \in \Theta(\text{number of leaves})$
- ▶ **Case 2:** Each layer has equal costs  
 $T(n) \in \Theta(n^{\log_b a} \log n)$ ,  $\log n$  layers
- ▶ **Case 3:** Connecting all partial solutions is *polynomial* bigger than solving all partial problems  
 $T(n) \in \Theta(f(n))$

# Further Literature

## ► General

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# Further Literature

- ▶ **Master theorem**

[Wik] [Master theorem](https://en.wikipedia.org/wiki/Master_theorem)

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