

Algorithms and Datastructures

Cache Efficiency, Divide and Conquer

Albert-Ludwigs-Universität Freiburg



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Algorithms and Datastructures, March 2016

Cache Efficiency

- Introduction

- Cache Organization

Divide and Conquer

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Background:

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- Up to now we always counted **number of operations**
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- Up to now we always counted **number of operations**
- Assuming this is a good measure for the runtime of a algorithm/tool
- Today we will see examples where this is not suitable

Example:

- We sum up all elements of a field a of size n in ...
 - natural order:

$$\text{sum}(a) = a[1] + a[2] + \dots + a[n]$$

- random order:

$$\text{sum}(a) = a[21] + a[5] + \dots + a[8]$$

Python:

```
def init(size):  
    # use system time as seed  
    random.seed(None)  
  
    # set linear order as accessor  
    order = [a for a in range(0, size)]  
  
    # init array with random data  
    data = [random.random() for a in order]  
  
    return (order, data)
```


Python:

```
def run(param):  
    # unpack data  
    (order, data) = param  
  
    # init the sum value  
    s = 0  
  
    for index in order:  
        s += data[index]  
  
    return s
```

Cache Efficiency

Linear Order

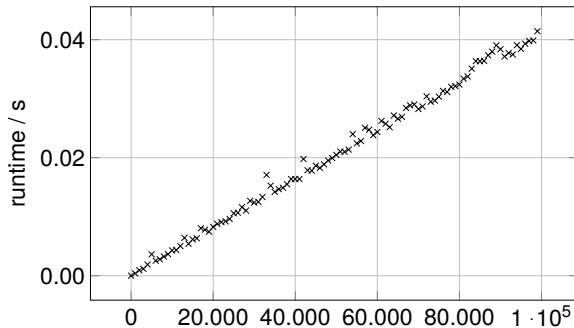


Figure: Summing elements in linear order

Python:

```
def init(size):  
    # use system time as seed  
    random.seed(None)  
  
    # set random order as accessor  
    order = [a for a in range(0, size)]  
    random.shuffle(order)  
  
    # init array with random data  
    data = [random.random() for a in order]  
  
    return (order, data)
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Cache Efficiency

Random Order



Figure: Summing elements in random order



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- Accessing elements in random order takes a lot longer (Factor 10)

Why?

- The costs in terms of memory access are very different

Cache Efficiency

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Cache Efficiency

CPU Cache



Cache Efficiency

CPU Cache



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- Accessing one or more byte/s of main memory loads a whole block ≈ 100 B into the cache

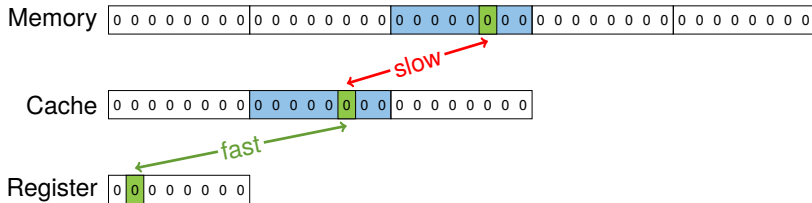


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- Accessing one or more byte/s of main memory loads a whole block ≈ 100 B into the cache
- As long as this block is in the cache, it is not necessary to access the memory for bytes of this block

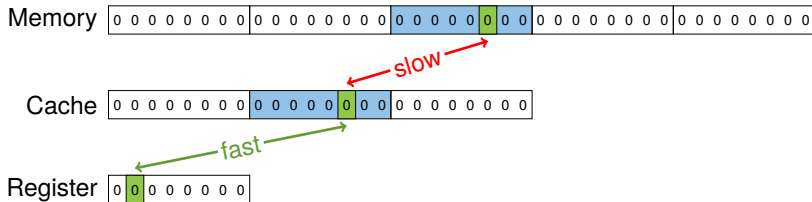
Cache Efficiency

CPU Cache



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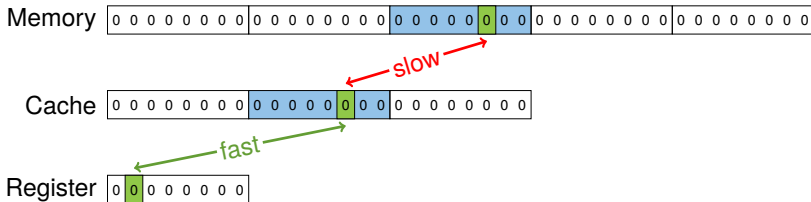
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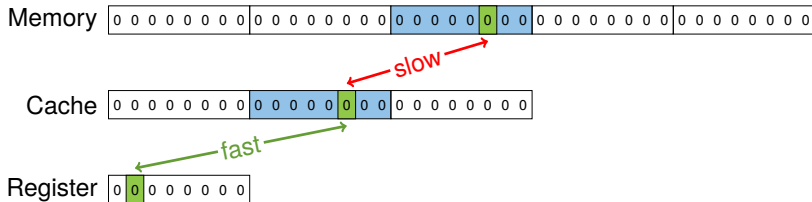
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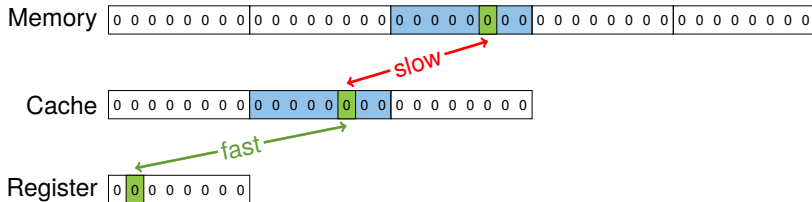
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Cache Efficiency

Block Operations



Terminology:



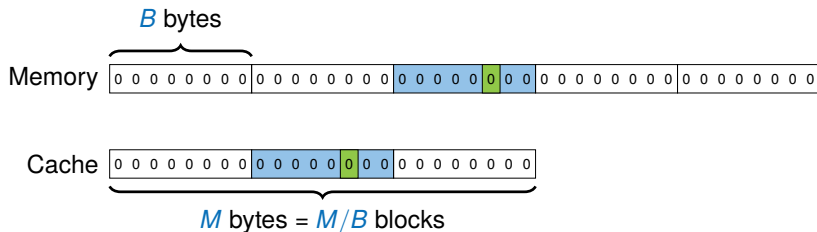
Terminology:

- The system consists of slow and fast memory



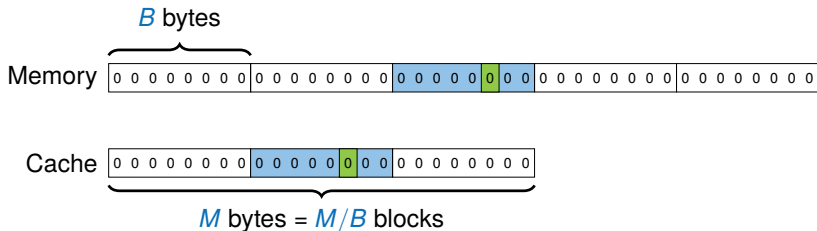
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- The **fast cache** has size M and can store M/B blocks
- If data is not in fast memory, the corresponding block is loaded into the **cache**

Cache Efficiency

Block Operations

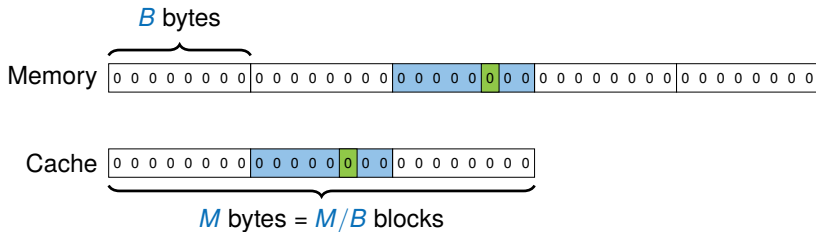


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- We ignore runtime costs of cache accesses / management

Block Operations



Figure: Comparison good / bad locality

Accessing the cache B times:

- **Best case:** 1 block operation \rightarrow good locality
- **Worst case:** B block operations \rightarrow bad locality



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Note:

- If the input size is smaller than M we load the complete data chunk directly into the cache
- Cache handling is only interesting when the input size is greater than M

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 - Many operating systems use free system memory as disk cache



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- These also fall under the term **cache efficiency** or **IO efficiency**



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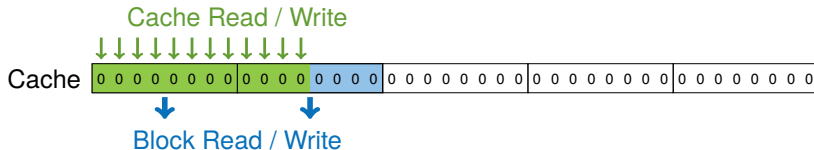


Figure: Good locality of sum operation



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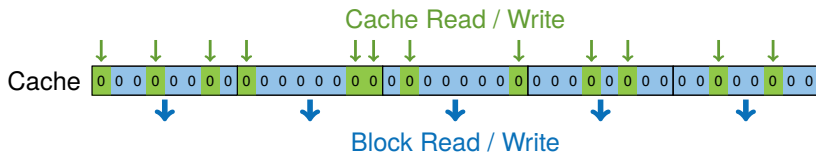


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- If **not $n \gg M$** the next element might already with a high probability loaded in cache



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Figure: QuickSort with pivot-element

- **at start:** pivot in first position, first re-arrange list such that left part contains small, right part larger elements
- do required changes *in place*



- **end point:** k is left to left-most element greater than pivot
swap position 0 (pivot) with k (smaller than pivot)

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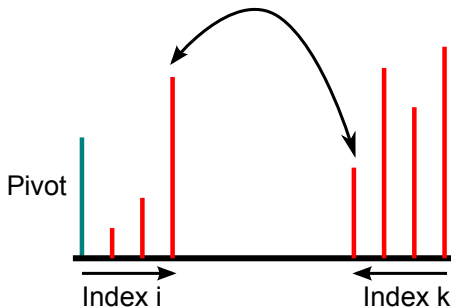
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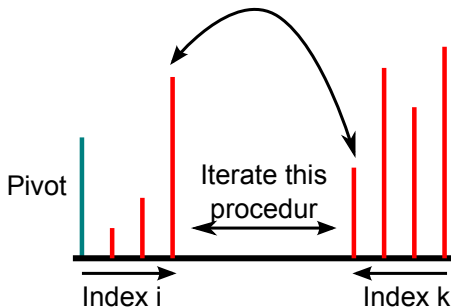
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Python:

```
def quicksort(l, start, end):  
    if (end - start) < 1:  
        return  
  
    i = start  
    k = end  
    piv = l[0]  
  
    ...
```

```
def quicksort(l, start, end):  
    ...  
  
    while k > i:  
        while l[i] <= piv and i <= end and k > i:  
            i += 1  
        while l[k] > piv and k >= start and k >= i:  
            k -= 1  
  
        if k > i: # swap elements  
            (l[i], l[k]) = (l[k], l[i])  
  
    (l[start], l[k]) = (l[k], l[start])  
    quicksort(l, start, k - 1)  
    quicksort(l, k + 1, end)
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- Assumptions:
 - Fields are always separated perfectly in the middle
 - n is a power of two and recursion depth is $k = \log_2 n$

$$\begin{aligned} T(n) &\leq \underbrace{A \cdot n}_{\text{splitting in two parts}} + \underbrace{2 \cdot T\left(\frac{n}{2}\right)}_{\text{recursive sort}} \\ &\leq A \cdot n + 2 \left(A \cdot \frac{n}{2} + 2 \cdot T\left(\frac{n}{4}\right) \right) \\ &= 2A \cdot n + 4 \cdot T\left(\frac{n}{4}\right) \\ &\leq 3A \cdot n + 8 \cdot T\left(\frac{n}{8}\right) \\ &\leq \dots \\ &\leq k \cdot A \cdot n + 2^k \cdot T(1) \\ &= \log_2 n \cdot A \cdot n + n \cdot T(1) \\ &\leq \log_2 n \cdot A \cdot n + n \cdot A \in \mathcal{O}(n \log_2 n) \end{aligned}$$

Cache Efficiency

Block Operations - QuickSort

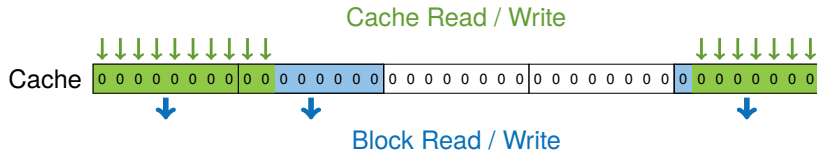


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- Let $IO(n)$ be the number of **block operations** for input size n
- Assumptions as before but recursion depth is $k = \log_2 \frac{n}{B}$
Why?

$$\begin{aligned} IO(n) &\leq \underbrace{A \cdot n/B}_{\text{splitting in two parts}} + \underbrace{2 \cdot IO(n/2)}_{\text{recursive sort}} \\ &\leq A \cdot n/B + 2(A \cdot n/2B + 2 \cdot IO(n/4)) \\ &\leq 2 \cdot A \cdot n/B + 4 \cdot IO(n/4) \\ &\leq 3 \cdot A \cdot n/B + 8 \cdot IO(n/8) \\ &\leq \dots \\ &\leq k \cdot A \cdot n/B + 2^k \cdot IO(n/2^k) \\ &= \log_2(n/B) \cdot A \cdot (n/B) + n/B \cdot IO(B) \\ &\leq \log_2(n/B) \cdot A \cdot (n/B) + A \cdot n/B \in O\left(\frac{n}{B} \cdot \log_2\left(\frac{n}{B}\right)\right) \end{aligned}$$

Cache Efficiency

Introduction

Cache Organization

Divide and Conquer

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Divide and Conquer

Introduction - Python



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```
def solve(problem):  
    if n < threshold:  
        # solve directly  
        return solution  
    else:  
        # divide problem into subproblems  
        # P1, P2, ..., Pk with k>=2  
        S1 = solve(P1)  
        S2 = solve(P2)  
        ...  
        Sk = solve(Pk)  
  
        # combine solutions  
    return S1 + S2 + ... + Sk
```

Divide and Conquer

Features



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- Recursion depth should not get too big (stack / memory overhead)

Divide and Conquer

Implementation



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Combination of solutions:

Division in subproblems:

- Choosing the number of subproblems and the concrete allocation can be demanding

Combination of solutions:

- Typically conceptual demanding

Divide and Conquer

Example - Maximum Subtotal



Example - Maximum Subtotal

Divide and Conquer

Example - Maximum Subtotal



Example - Maximum Subtotal Input:

Divide and Conquer

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- Progression X of n integers

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- Maximum sum of related subsequence and its index boundary

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

Example - Maximum Subtotal Input:

- Progression X of n integers

Output:

- Maximum sum of related subsequence and its index boundary

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

Application:

- Maximum profit of buying and selling shares





Naive solution (brute force)

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```
def maxSubArray(X):  
    # Store sum, start, end  
    result = (X[0], 0, 0)  
    for i in range(0, len(X)):  
        for j in range(i, len(X)):  
            subSum = 0  
            for k in range(i, j + 1):  
                subSum += X[k]  
            if result[0] < subSum:  
                result = (subSum, i, j)  
    return result
```

Divide and Conquer

Example - Maximum Subtotal - Python



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Runtime - Upper bound

Runtime - Upper bound

```
def maxSubArray(X):  
    result = (X[0], 0, 0)  
    # n loops -> O(n)  
    for i in range(0, len(X)):  
        # max n loops -> O(n)  
        for j in range(i, len(X)):  
            # max n loops -> O(n)  
            subSum = sum(X[i:j+1])  
            if result[0] < subSum: # O(1)  
                result = (subSum, i, j)  
    return result
```

Divide and Conquer

Example - Maximum Subtotal



Upper bound:



Upper bound:

- Three interleaved loops



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- Each loop with runtime $O(n)$

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- Each loop with runtime $O(n)$
- Algorithm runtime of $O(n^3)$

Lower bound:

Table: Operations

i	Additions	j
$\frac{n}{3} \in O(n)$	$\frac{n}{3} \in O(n)$	$\frac{n}{3} \in O(n)$

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- For each i we iterate at least $\frac{n}{3}$ values for j

Lower bound:

Table: Operations

i	Additions	j
$\frac{n}{3} \in O(n)$	$\frac{n}{3} \in O(n)$	$\frac{n}{3} \in O(n)$

- We iterate at least $\frac{n}{3}$ values for i
- For each i we iterate at least $\frac{n}{3}$ values for j
- For each j we have at least $\frac{n}{3}$ additions

Lower bound:

Table: Operations

i	Additions	j
$\frac{n}{3} \in O(n)$	$\frac{n}{3} \in O(n)$	$\frac{n}{3} \in O(n)$

- We iterate at least $\frac{n}{3}$ values for i
- For each i we iterate at least $\frac{n}{3}$ values for j
- For each j we have at least $\frac{n}{3}$ additions
- We need at least $T(n) = (\frac{n}{3})^3 \in \Omega(n^3)$ steps

Divide and Conquer

Example - Maximum Subtotal - Runtime



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Runtime:

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- With $T(n) \in O(n^3)$ and $T(n) \in \Omega(n^3)$ we know:

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- It is hard to solve the problem in a worse way ...

Divide and Conquer

Example - Maximum Subtotal - Runtime



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Current approach:

Current approach:

- Calculating the sum for range from i to j with loop

$$S_{i,j} = X[i] + X[i+1] + \dots + X[j]$$

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Better approach:

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- Calculating the sum for range from i to j with loop

$$S_{i,j} = X[i] + X[i+1] + \dots + X[j]$$

Better approach:

- Incremental sum instead of loop

$$S_{i,j+1} = X[i] + X[i+1] + \dots + X[j] + X[j+1]$$

$$S_{i,j+1} = S_{i,j} + X[j+1] \in O(1) \quad \text{instead of} \quad \in O(n)$$

Divide and Conquer

Example - Maximum Subtotal - Python



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Better solution:

Better solution:

```
def maxSubArray(X):  
    result = (X[0], 0, 0)  
    # n loops -> O(n)  
    for i in range(0, len(X)):  
        subSum = 0  
        # max n loops -> O(n)  
        for j in range(i, len(X)):  
            subSum += X[j] # O(1)  
            if result[0] < subSum: # O(1)  
                result = (subSum, i, j)  
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Better solution:

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def maxSubArray(X):  
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            subSum += X[j] # O(1)  
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■ Runtime $\in O(n^2)$

Divide and Conquer

Example - Maximum Subtotal



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Divide and Conquer:



Divide and Conquer Idea to solve:

- split the sequence in the middle

Divide and Conquer

Example - Maximum Subtotal

Divide and Conquer:



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- Solve the left half of the problem

Divide and Conquer

Example - Maximum Subtotal



Divide and Conquer:



Divide and Conquer Idea to solve:

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- Solve the left half of the problem
- Solve right half and combine both solutions into a total solution

Divide and Conquer

Example - Maximum Subtotal

Divide and Conquer:



Divide and Conquer Idea to solve:

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- Solve the left half of the problem
- Solve right half and combine both solutions into a total solution
- OK if maximum is located in left half (*A*) or right half (*B*)

Divide and Conquer:



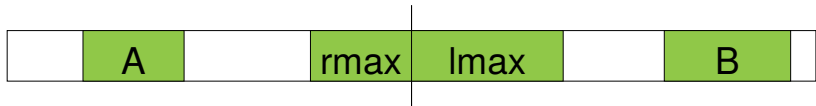
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Divide and Conquer

Example - Maximum Subtotal

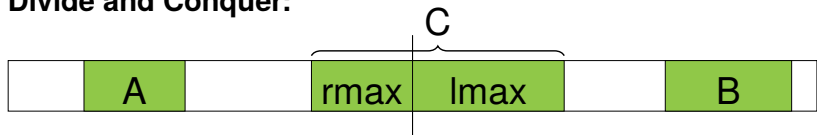
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- The overall solution is the **maximum of A, B and C**

Divide and Conquer

Example - Maximum Subtotal



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

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- Bigger problems are partitioned into two subproblems and recursively solved. Subsolutions A and B are returned.
- To determine subsolution C, rmax and lmax for the subproblems are computed.

Principle - Divide and Conquer:

- Small problems are solved directly: $n = 1 \Rightarrow \text{max} = X[0]$
- Bigger problems are partitioned into two subproblems and recursively solved. Subsolutions A and B are returned.
- The overall solution is the maximum of A, B and C

Divide and conquer solution

```
def maxSubArray(X, i, j):  
    if i == j: #trivial case  
        return (X[i], i, i)  
    m = (i + j) / 2  
    #recursive Subsolutions for A,B  
    A = maxSubArray(X, i, m)  
    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])  
    #Solution results from A,B,C  
    return max([A, B, C], \  
               key=lambda item: item[0])
```

■ General

[CRL01] Thomas H. Cormen, Ronald L. Rivest, and Charles E. Leiserson.

Introduction to Algorithms.

MIT Press, Cambridge, Mass, 2001.

[MS08] Kurt Mehlhorn and Peter Sanders.

Algorithms and data structures, 2008.

<https://people.mpi-inf.mpg.de/~mehlhorn/ftp/Mehlhorn-Sanders-Toolbox.pdf>.

■ Caching

[Wik] [Cache](https://en.wikipedia.org/wiki/Cache)

`https://en.wikipedia.org/wiki/Cache`