Algorithmns and Datastructures

Cache Efficiency, Divide and Conquer

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Algorithmns and Datastructures, March 2016

Structure

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Background:

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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

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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:

$$\mathrm{sum}(a) = a[1] + a[2] + \cdots + a[n]$$

  - random order:

$$\mathrm{sum}(a) = a[21] + a[5] + \cdots + a[8]$$

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:

```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

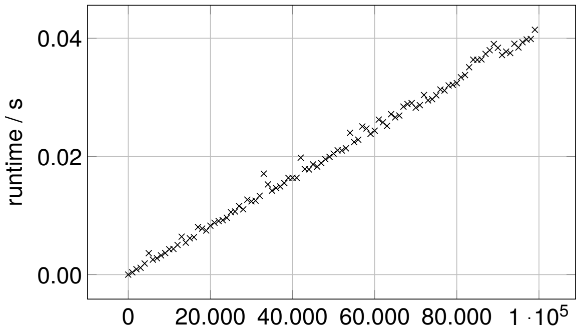

Figure: Summing elements in linear order

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
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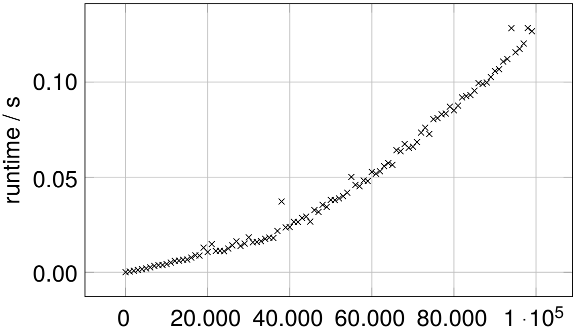

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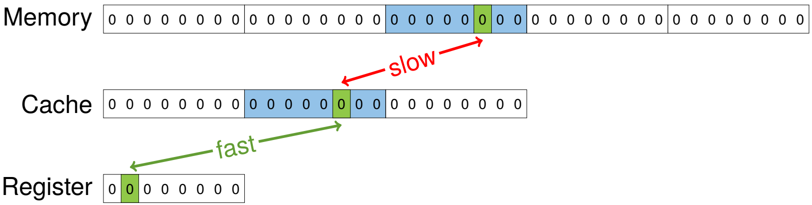
- Accessing elements in random order takes a lot longer (Factor 10)
  Why?
- The costs in terms of memory access are very different

Structure

Cache Efficiency
CPU Cache



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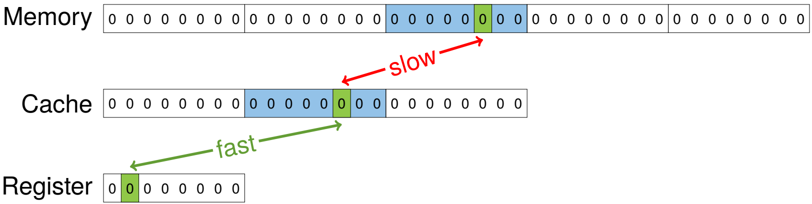
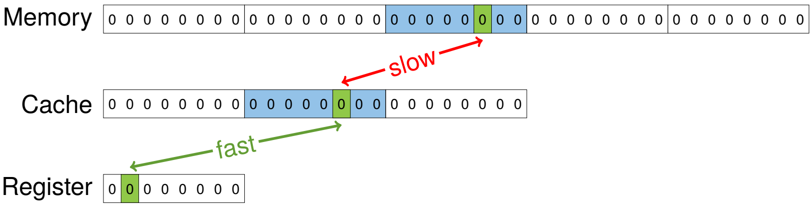


Principle / organization:



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Cache Efficiency
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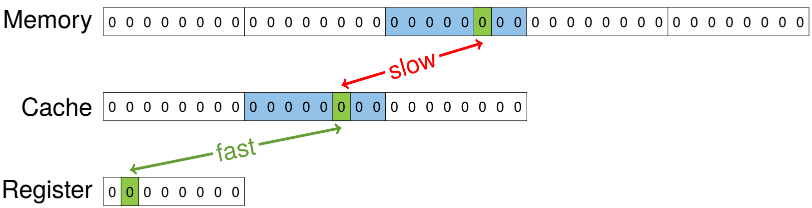

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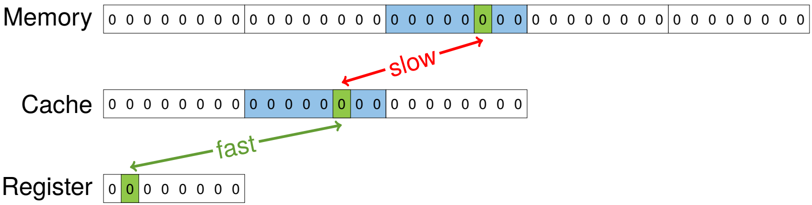

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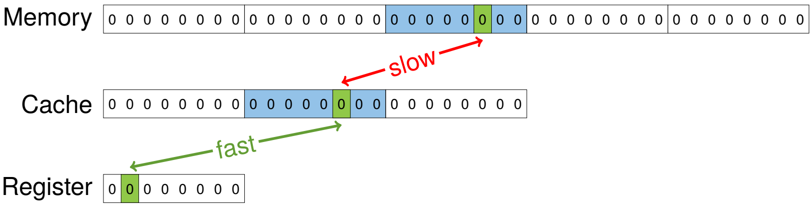

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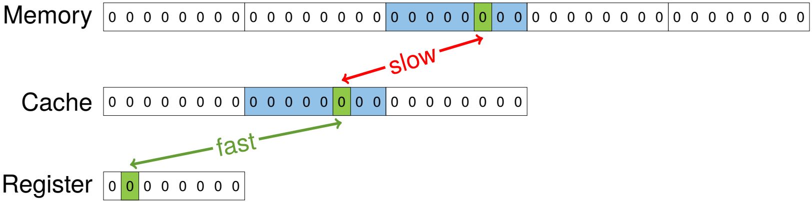
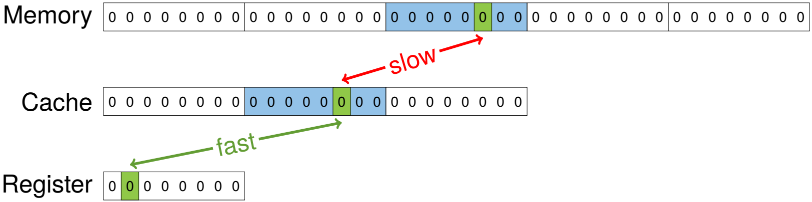
- As long as this block is in the cache, it is not neccessary to access the memory for bytes of this block

Cache Efficiency

CPU Cache





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Cache Efficiency

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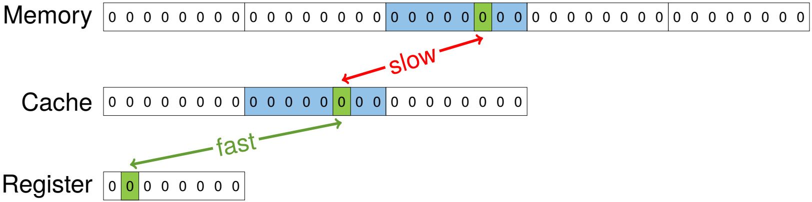

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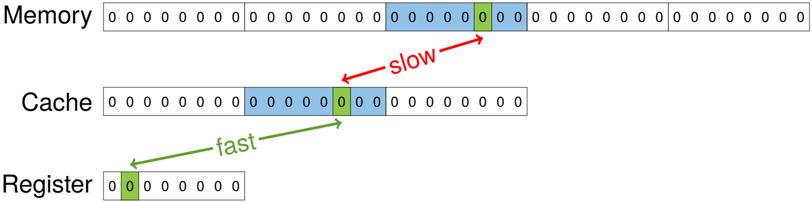

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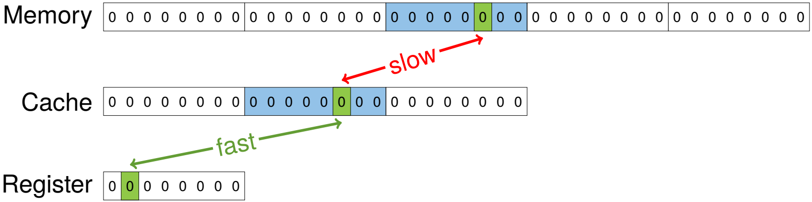

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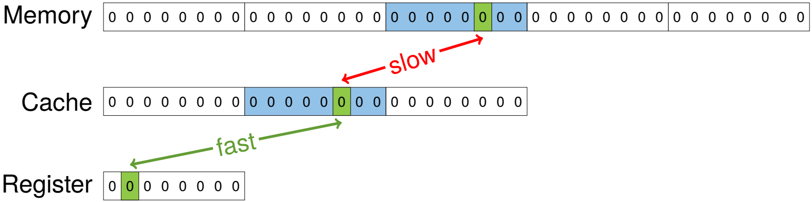

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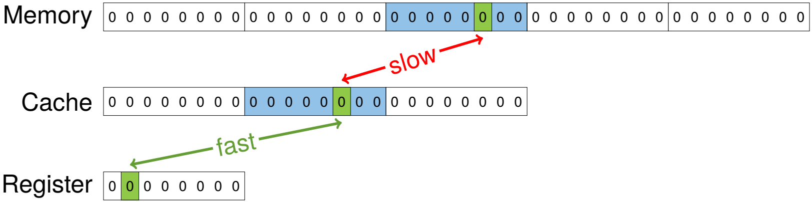

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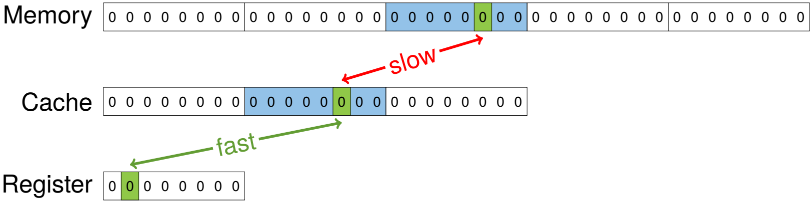

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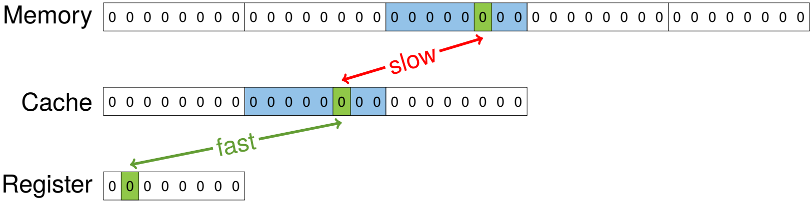

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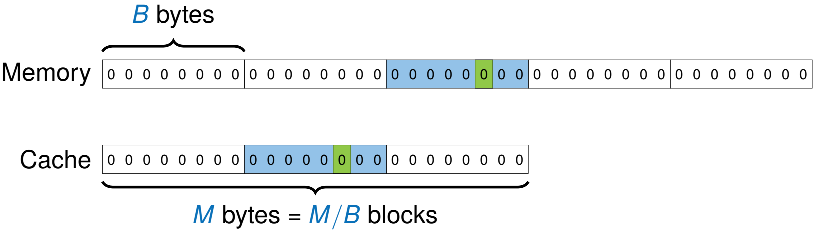
  - First in first out (FIFO)
- Details of discarding are not the topic for today

Cache Efficiency

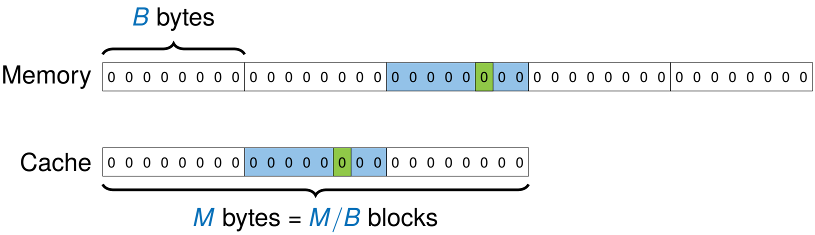
Block Operations



Terminology:

Cache Efficiency

Block Operations



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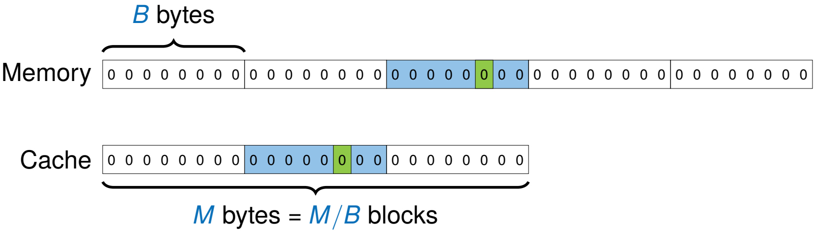

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Cache Efficiency

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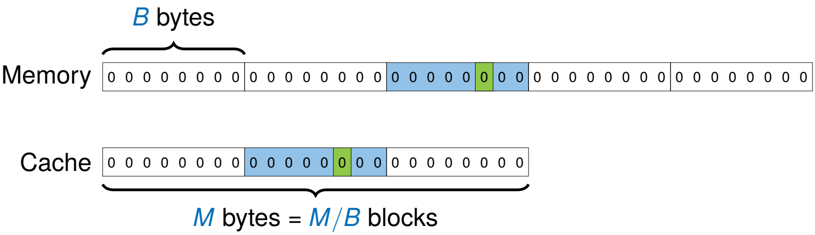

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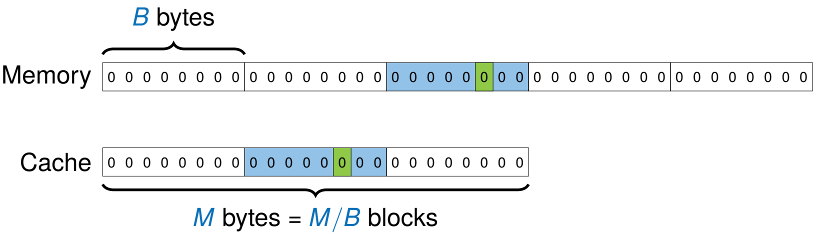

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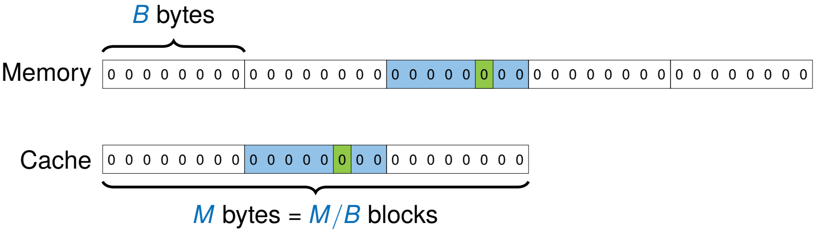
Cache Efficiency

Block Operations



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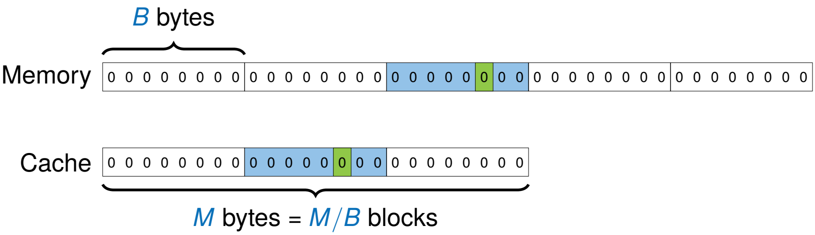

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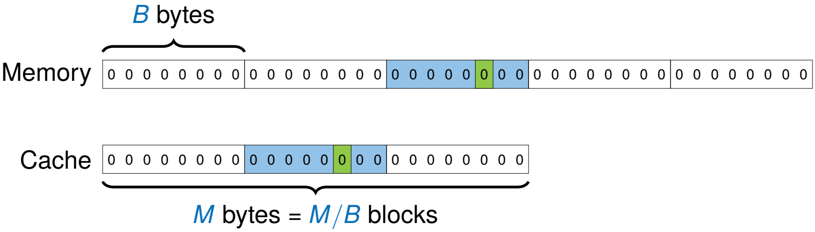

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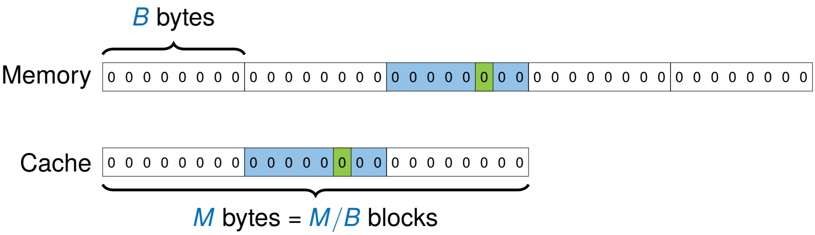

Terminology:

- The program defines which blocks are held in the cache
- We use the number of block operations as runtime estimation
- We ignore runtime costs of cache accesses / management

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:

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- Cache handling is only interesting when the input size is greater than M

Typical values: (`Intel© i7-4770` Haswell, `WD© Blue` 2 TB)

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- Disk Cache: $B = 64\,\text{kB}$, $M = 64\,\text{MB}$
  - Many operating systems use free system memory as disk cache

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- Block operations on disk-cache are called IOs (input / output operations)
- These also fall under the term cache efficiency or IO efficiency

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Cache Efficiency

Block Operations - Linear Order

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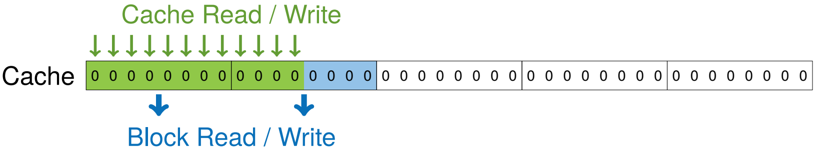

Figure: Good locality of sum operation

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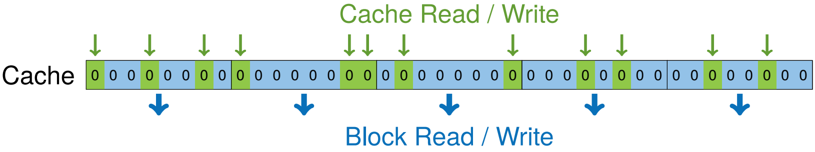

Figure: Bad locality of sum operation

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Cache Efficiency

Block Operations - QuickSort

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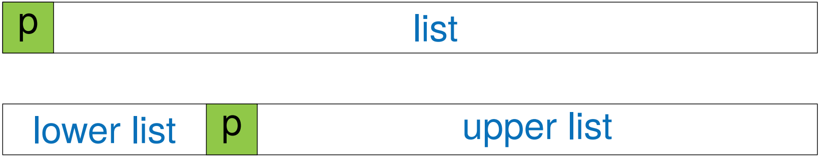

Figure: *QuickSort* with pivot-element

Idea of Quicksort

- **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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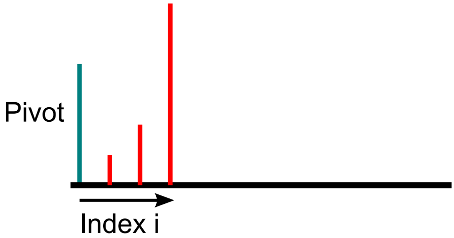

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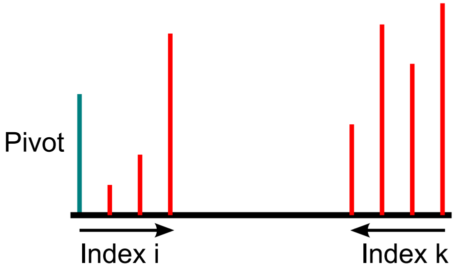

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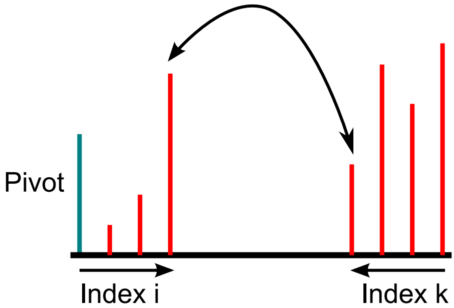

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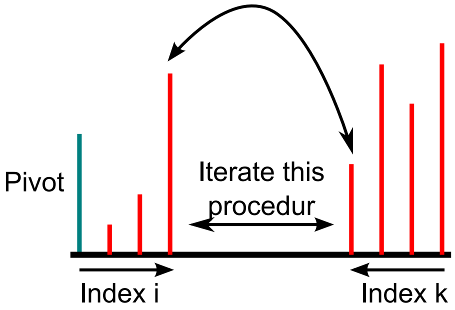

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Python:

```
def quicksort(l, start, end):
  if (end - start) < 1:
    return

  i = start
  k = end
  piv = l[0]

  ...
```

```python
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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    - n is a power of two and recursion depth is $k = \log_2 n$

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

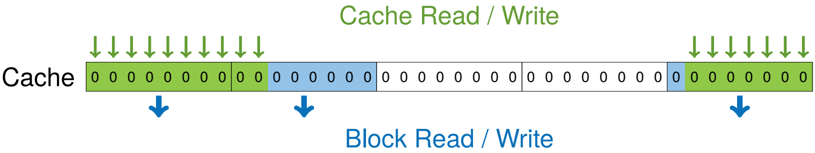

Figure: Locality of quicksort

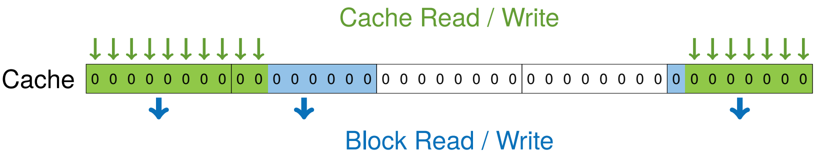

Figure: Locality of quicksort

- Let $IO(n)$ be the number of block operations for input size n

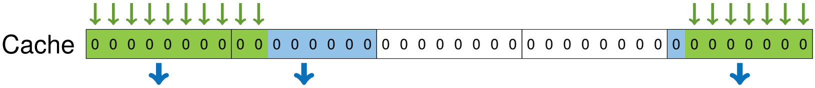

Figure: Locality of quicksort

- 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?

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

Structure

Cache Efficiency

Introduction

Cache Organization

Divide and Conquer

Introduction

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- Recursive application of the algorithm to ever smaller subproblems
- Direct solving of sufficently small subproblems

- Function solve for solving a problem of size n

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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

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- Suitable for parallel processing
  - Subproblems are independent of each other
  - Only needed input for each subproblem has to be known

Definition of the trivial case:

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

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- Typically conceptional demanding

Example - Maximum Subtotal

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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

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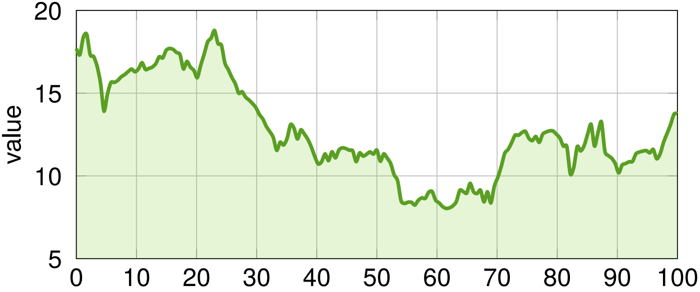
Index	0	1	2	3	4	5	6	7	8	9
Value	31	-41	59	26	-53	58	97	-93	-23	84

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

Application:

- Maximum profit of buying and selling shares



Naive solution (brute force)

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Naive solution (brute force)

```
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
```

Runtime - Upper bound

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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
```

Upper bound:

Upper bound:

- Three interleaved loops

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- Each loop with runtime $O(n)$

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Upper bound:

- Three interleaved loops
- 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
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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

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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 ...

Current approach:

Current approach:

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

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

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Better approach:

Current approach:

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

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

Better approach:

- Incremental sum instead of loop

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

Better solution:

Divide and Conquer

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Better solution:

```python
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)):
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```
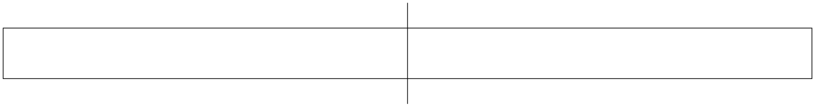

- Runtime $\in O(n^2)$

Divide and Conquer

Example - Maximum Subtotal

Divide and Conquer:



Divide and Conquer Idea to solve:

- split the sequence in the middle

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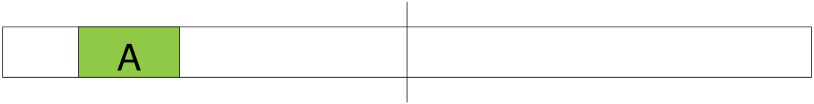

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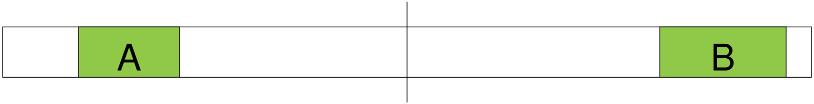
Divide and Conquer:



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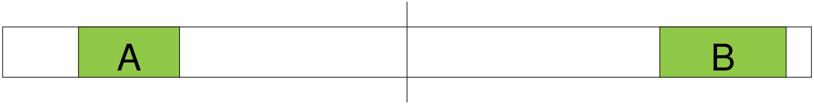

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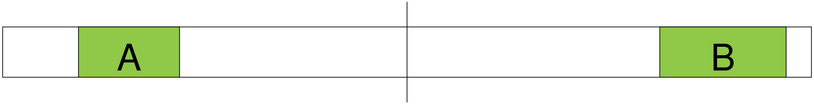

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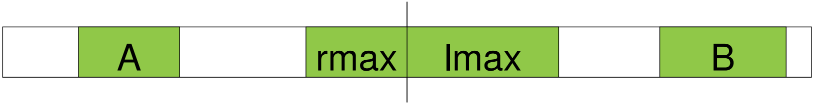

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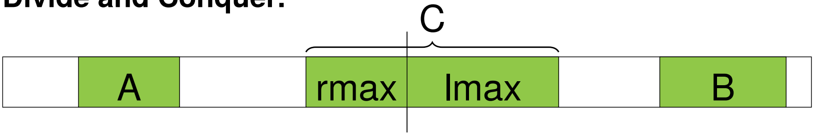

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Divide and conquer solution

```
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])
```

Further Literature

- **General**

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Further Literature

- **Caching**

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