Entwurf, Analyse und Umsetzung von Algorithmen

Cache Efficiency, Divide and Conquer

Albert-Ludwigs-Universität Freiburg

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Entwurf, Analyse und Umsetzung von Algorithmen

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intelligente eingebettete
mikrosysteme

Structure

Cache Efficiency
- Introduction
- Cache Organization

Divide and Conquer
- Introduction

Background:

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- Up to now we always counted the number of operations
- Assuming this is a good measure for the runtime of an algorithm/tool

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

Example:

- We sum up all elements of an array 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):
    """Creates the dataset."""

    # 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):
    """Processes the dataset."""

    # unpack data
    (order, data) = param

    # init the sum value
    s = 0

    for index in order:
        s += data[index]

    return s
```

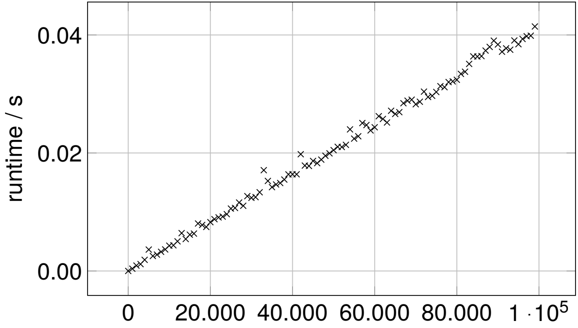

Figure: summing elements in linear order

Cache Efficiency

Random Order - Python

```
def init(size):
    """Creates a randomly ordered dataset."""

    # 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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    return (order, data)
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Cache Efficiency
Random Order

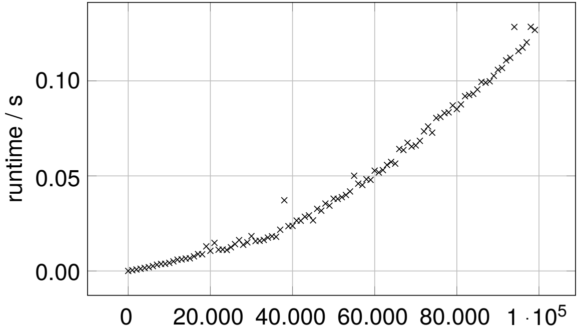

Figure: summing elements in random order

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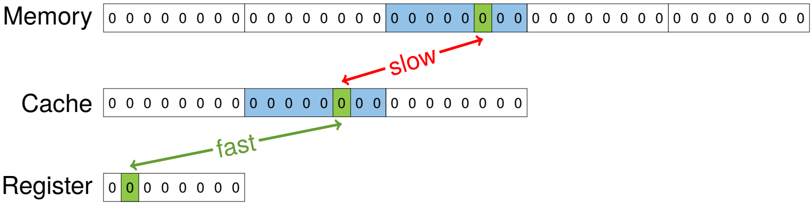
- Accessing elements in random order takes a lot longer (factor 10) Why?
- The costs in terms of memory access are very different

Structure

Cache Efficiency
CPU Cache



Cache Efficiency

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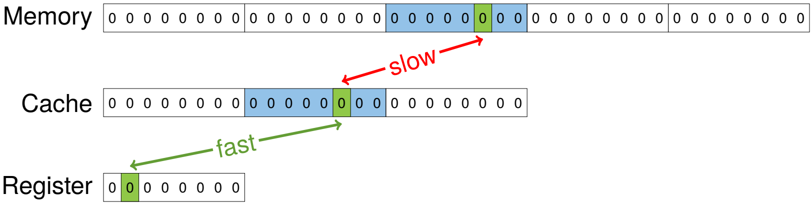

Principle / organization:

Cache Efficiency

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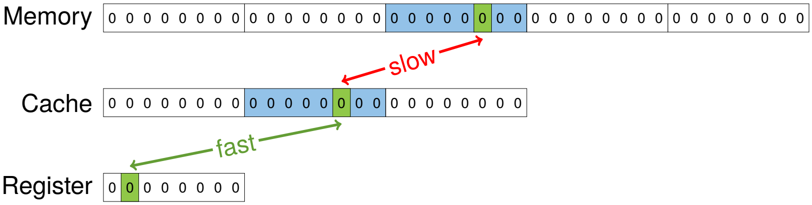

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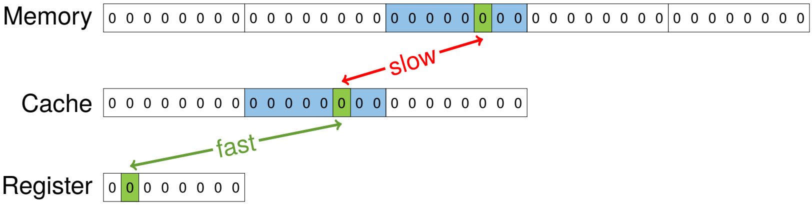
- Accessing one byte of the main memory takes $\approx 100\,\text{ns}$



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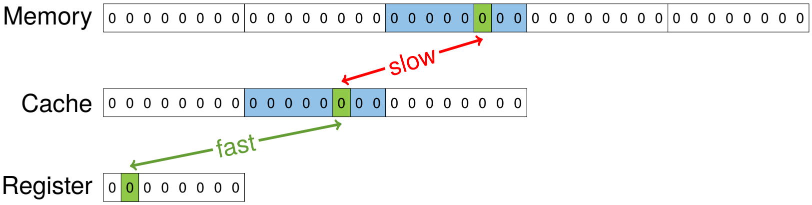

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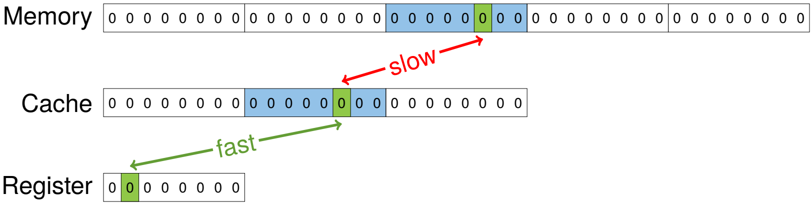

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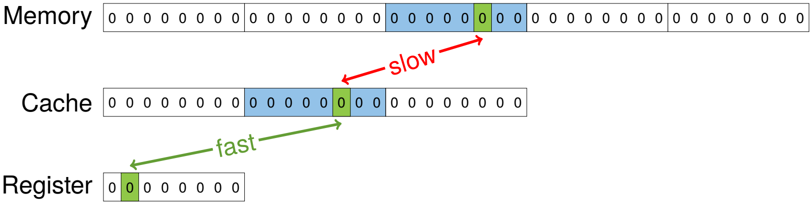
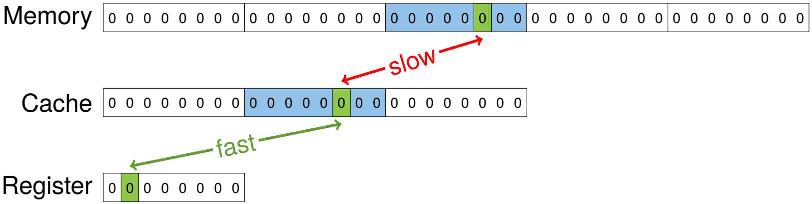
- As long as this block is in the cache, it is not neccessary to access the memory for bytes of this block

Cache Efficiency
CPU Cache





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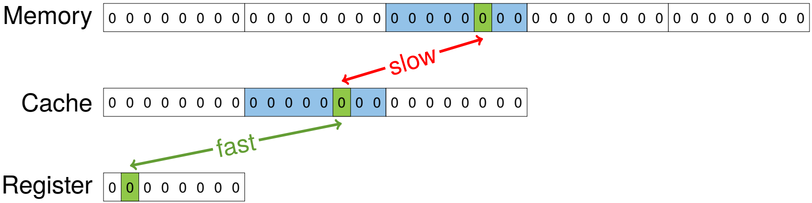

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Cache Efficiency

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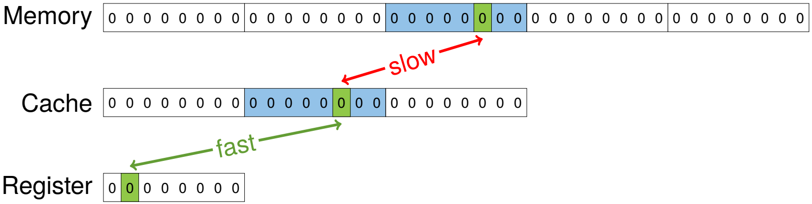

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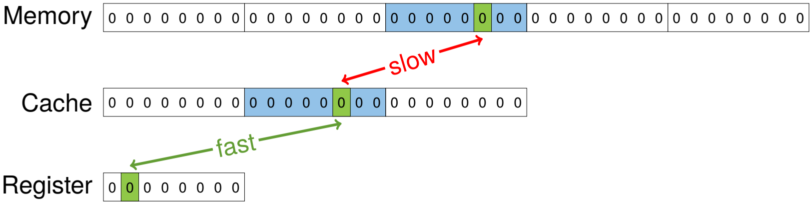

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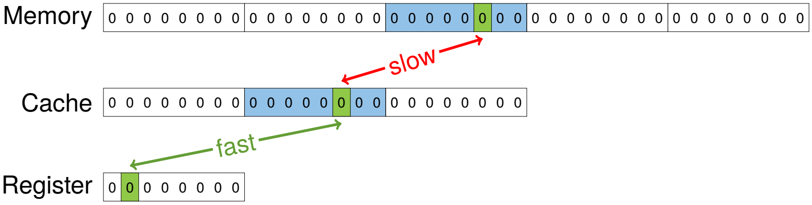

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Cache Efficiency

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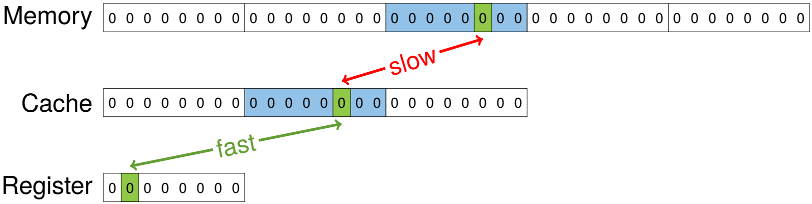

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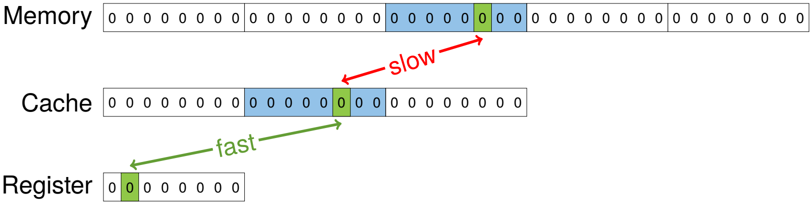

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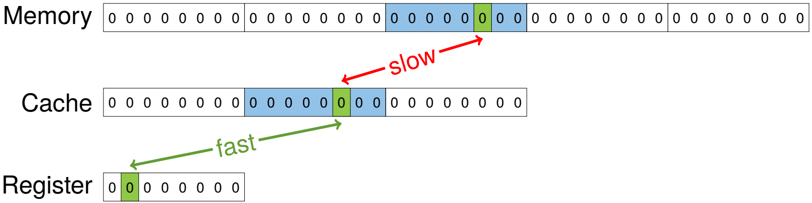

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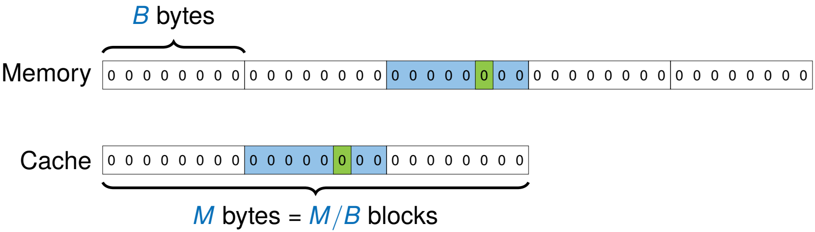
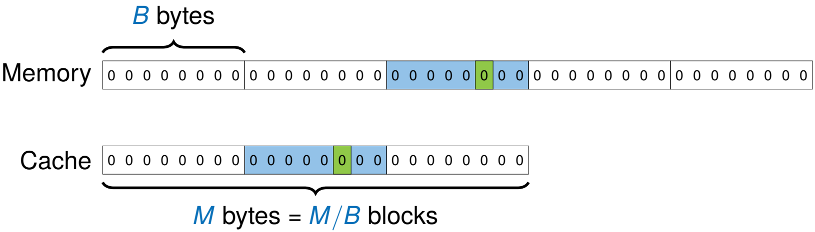
- Details of discarding not discussed today

Cache Efficiency
Block Operations



Terminology:



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Cache Efficiency

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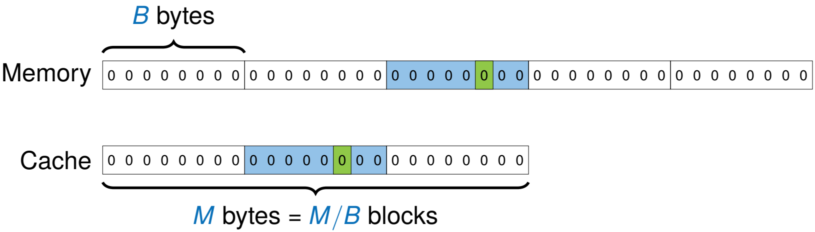

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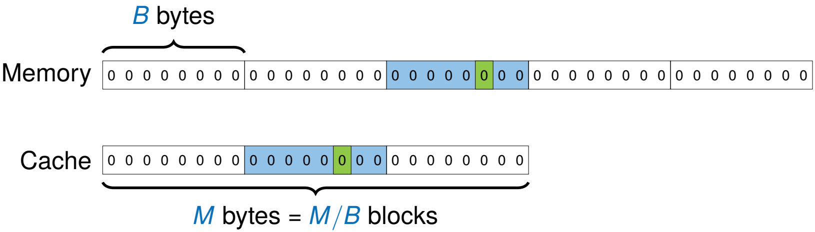

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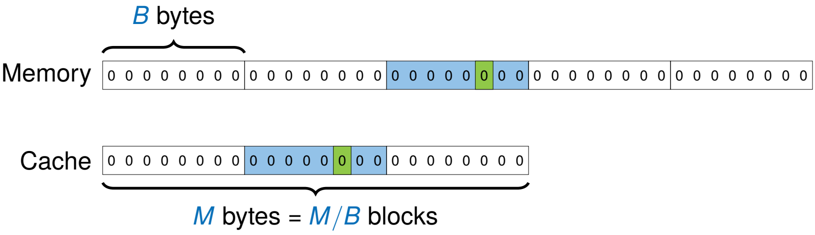

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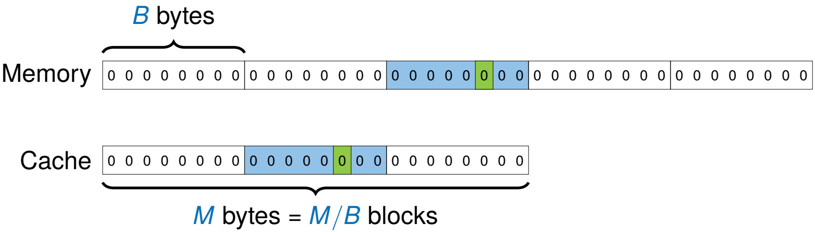
- If data is not in fast memory, the corresponding block is loaded into the cache

Cache Efficiency
Block Operations



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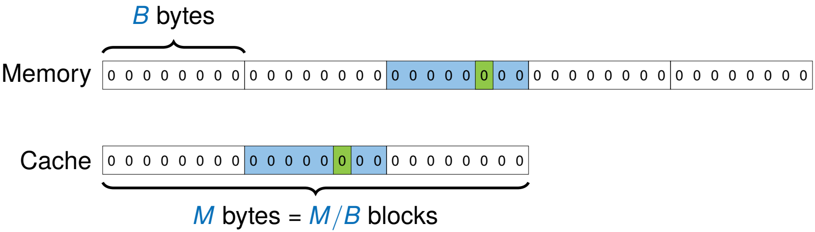

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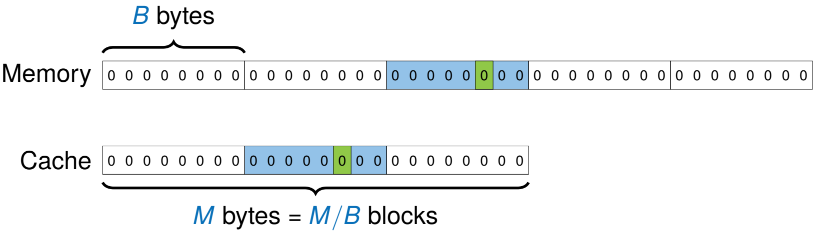

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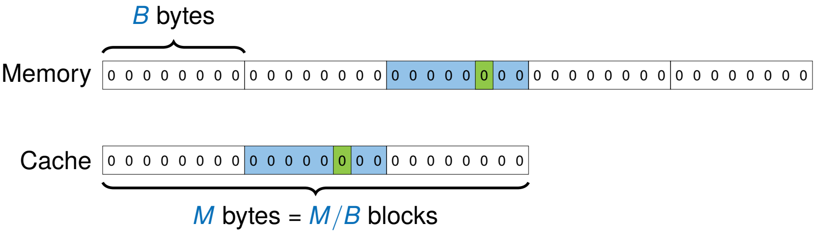

Terminology:

- 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 access / management

Figure: comparison good / bad locality

Accessing the cache *B* times:

- Best case: 1 block operation → good locality
- Worst case: *B* block operations → 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 loads on CPU cache are called cache misses
- 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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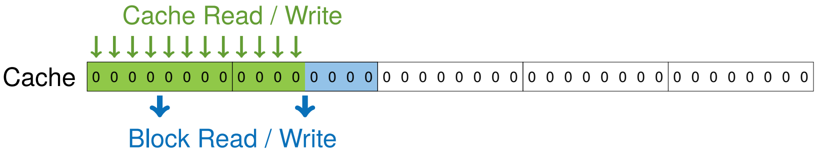

Figure: good locality of sum operation

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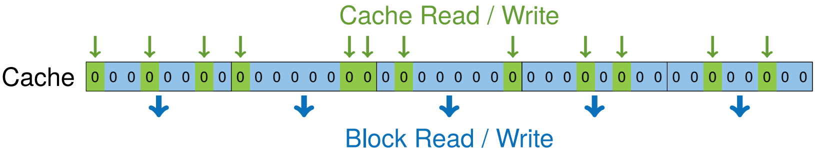

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- If not $n \gg M$ this might occur with a high probability

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 smaller and 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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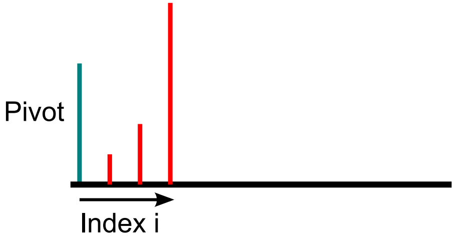

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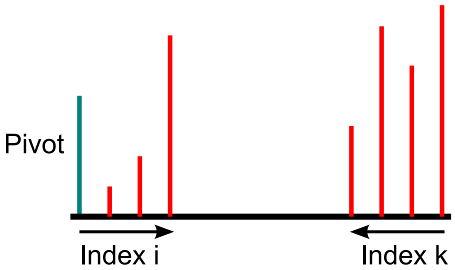

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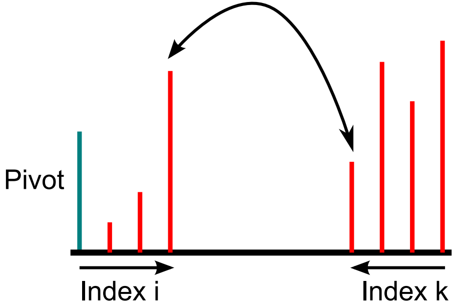

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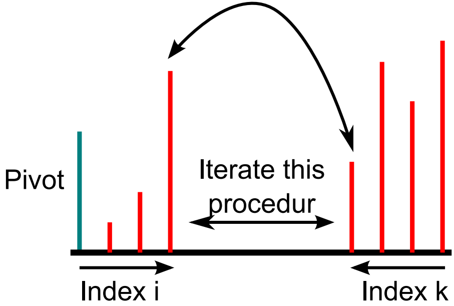

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Python:

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

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

  ...
```

Cache Efficiency

Block Operations - Quicksort - 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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- Arrays are always separated perfectly in the middle
- n is a power-of-two and recursion depth is $k = \log_2 n$

Cache Efficiency
Block Operations - Quicksort

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

Cache Efficiency

Block Operations - Quicksort

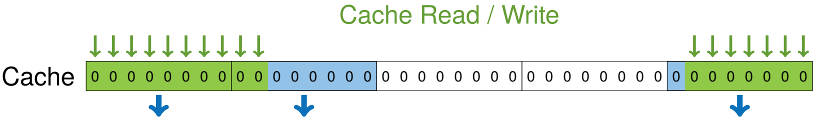

Figure: locality of Quicksort

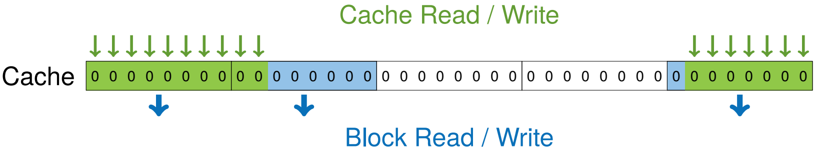

Figure: locality of Quicksort

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

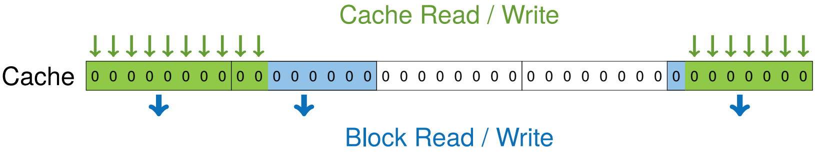

Figure: locality of Quicksort

- 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?

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

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 sufficiently small subproblems

- Function solve for solving a problem of size n

- Function solve for solving a problem of size *n*

```
def solve(problem):
    if n < threshold:
        return solution # solve directly
    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
```

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- Suitable for parallel processing
  - Parallel processing of subproblems possible since subproblems are independent of each other

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Definition of the trivial case:

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- Smaller subproblems are elegant and simple

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- Smaller subproblems are elegant and simple
- On the other hand the efficiency will be improved if relatively big subproblems can be solved directly
- Recursion depth should not get too big (stack / memory overhead)

Division in subproblems:

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Combination of solutions:

- Typically conceptionally 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

Example - Maximum Subtotal Input:

- Sequence X of n integers

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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

Figure: stock value over time

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

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 nested loops

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Upper bound:

- Three nested 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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$\frac{n}{3} \in O(n)$	$\frac{n}{3} \in O(n)$	$\frac{n}{3} \in O(n)$

- 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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- 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 …

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Current approach:

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- 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:

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

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:

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

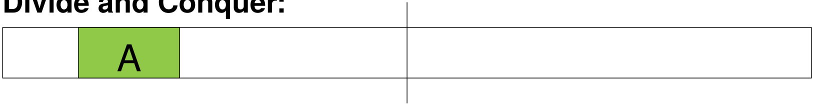
- Runtime $\in O(n^2)$

Divide and Conquer:

Divide and Conquer idea to solve:

- Split the sequence in the middle

Divide and Conquer:



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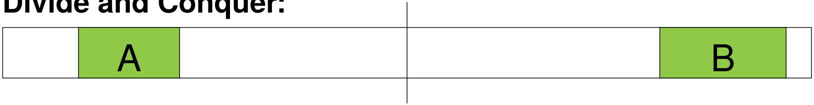

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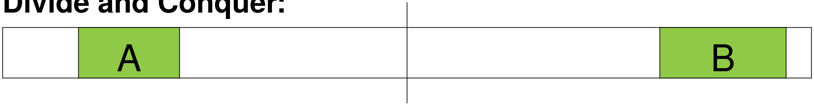

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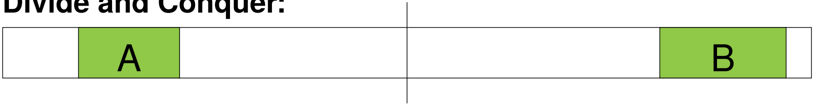

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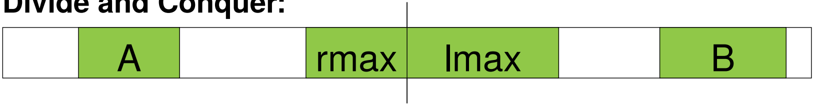

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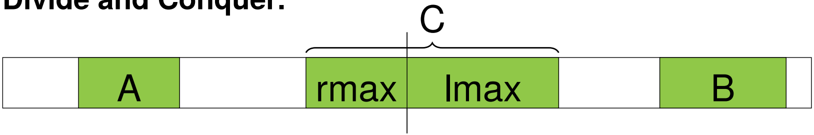

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```python
def maxSubArray(X, i, j):
    if i == j: # trivial case
        return (X[i], i, i)

    # recursive subsolutions for A, B
    m = (i + j) // 2
    A = maxSubArray(X, i, m)
    B = maxSubArray(X, m + 1, j)

    # rmax and lmax for cornercase 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])
```

Further Literature

- **General**

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Further Literature

- **Caching**

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