

COMP526 (Spring 2022) University of Liverpool version 2022-02-24 22:54

Learning Outcomes

- 1. Know principles and implementation of *mergesort* and *quicksort*.
- 2. Know properties and *performance characteristics* of mergesort and quicksort.
- **3.** Know the comparison model and understand the corresponding *lower bound*.
- **4.** Understand *counting sort* and how it circumvents the comparison lower bound.
- 5. Know ways how to exploit *presorted* inputs.
- **6.** Understand and use the *parallel random-access-machine* model in its different variants.
- Be able to *analyze* and compare simple shared-memory parallel algorithms by determining *parallel time and work*.
- 8. Understand efficient parallel *prefix sum* algorithms.
- *9.* Be able to devise high-level description of *parallel quicksort and mergesort* methods.

Unit 3: Efficient Sorting



Outline



- 3.1 Mergesort
- 3.2 Quicksort
- 3.3 Comparison-Based Lower Bound
- 3.4 Integer Sorting
- 3.5 Adaptive Sorting
- 3.6 Python's list sort
- 3.7 Parallel computation
- 3.8 Parallel primitives
- 3.9 Parallel sorting

Why study sorting?

- fundamental problem of computer science that is still not solved
- building brick of many more advanced algorithms
 - for preprocessing
 - as subroutine
- playground of manageable complexity to practice algorithmic techniques

Here:

- "classic" fast sorting method
- exploit partially sorted inputs
- parallel sorting

— Algorithm with optimal #comparisons in worst case?

Part I *The Basics*

Rules of the game

Given:

• array A[0..n) = A[0..n-1] of *n* objects

▶ a total order relation ≤ among A[0],...,A[n - 1] (a comparison function) Python: elements support <= operator (_le_()) Java: Comparable class (x.compareTo(y) <= 0)</pre>

► **Goal:** rearrange (i. e., permute) elements within *A*, so that *A* is *sorted*, i. e., $A[0] \le A[1] \le \cdots \le A[n-1]$

for now: A stored in main memory (internal sorting) single processor (sequential sorting)

Clicker Question

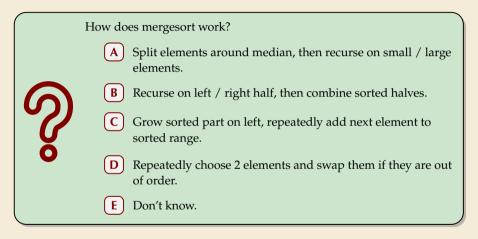


What is the complexity of sorting? Type you answer, e.g., as "Theta(sqrt(n))"



3.1 Mergesort

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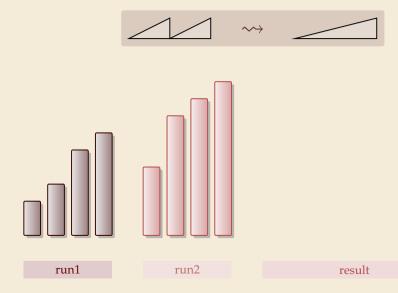


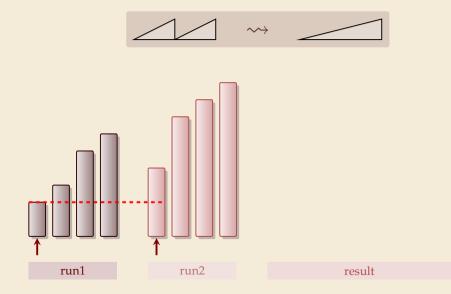
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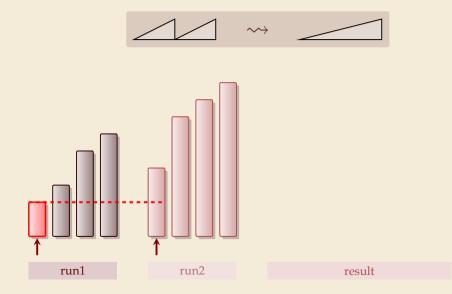
| | How does mergesort work? |
|--------------|---|
| | A Split elements around median, then recurse on small / large elements. |
| 6 | B Recurse on left / right half, then combine sorted halves. \checkmark |
| ^v | C Grew sorted part on left, repeatedly add next element to sorted range. |
| 0 | D Repeatedly choose 2 elements and swap them if they are out of order. |
| | E Don't know. |

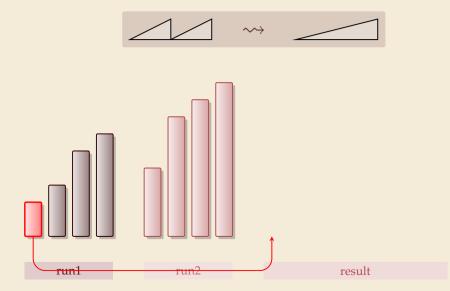


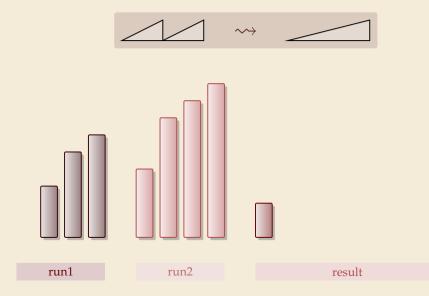
 $\sim \rightarrow$

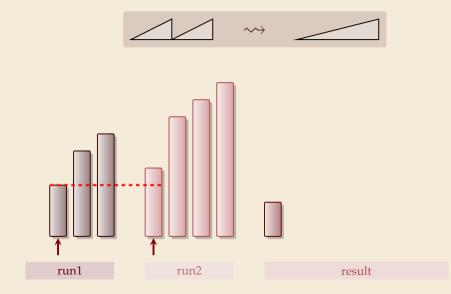


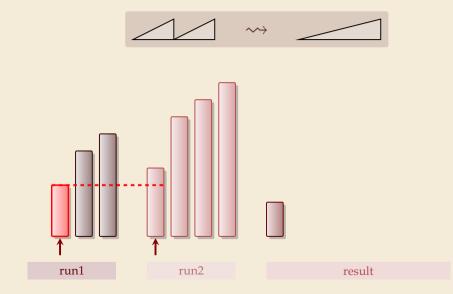


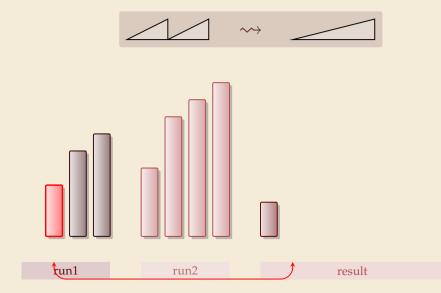


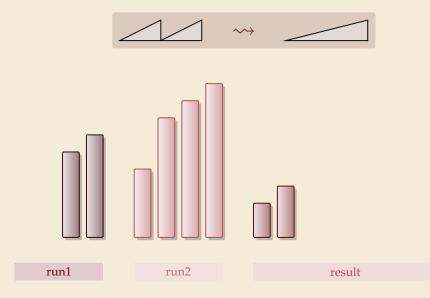


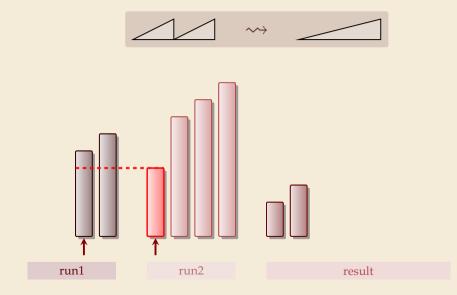


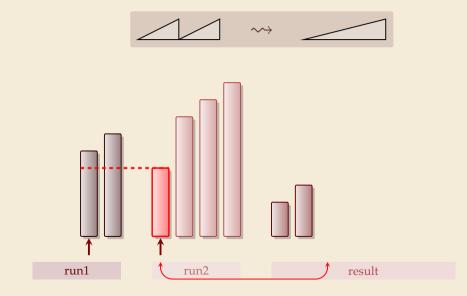


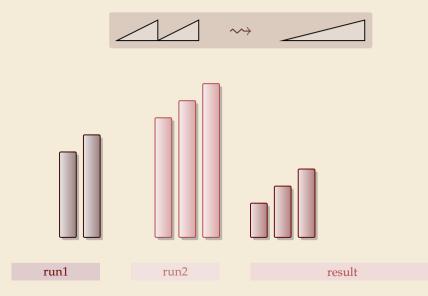


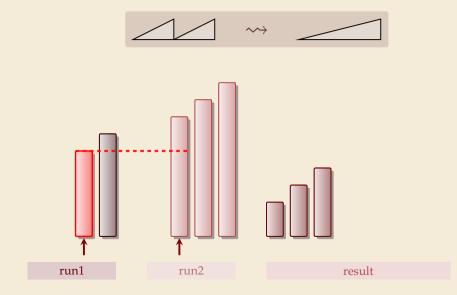


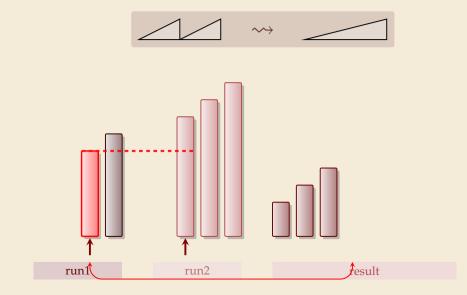


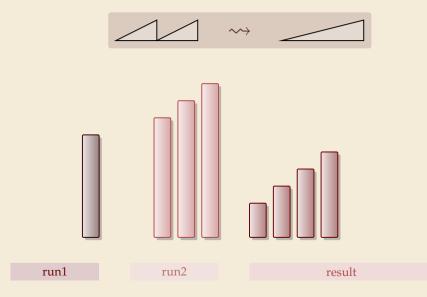


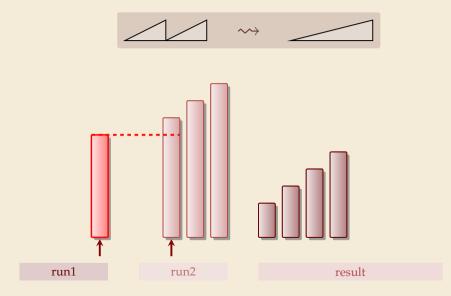


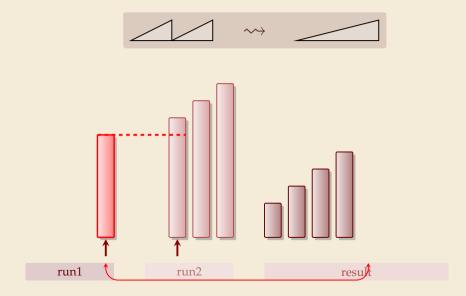




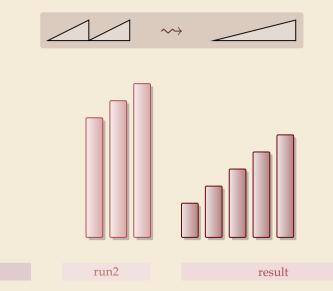




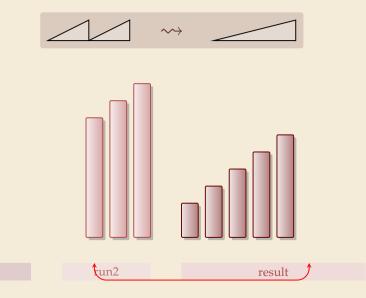


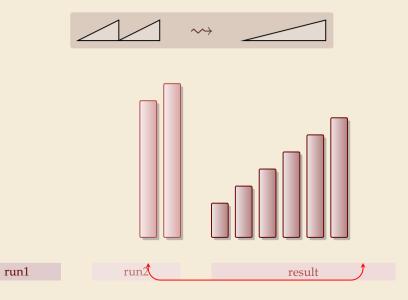


run1



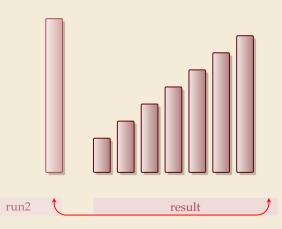
run1



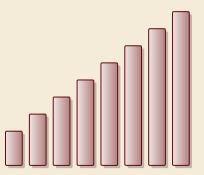


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run1

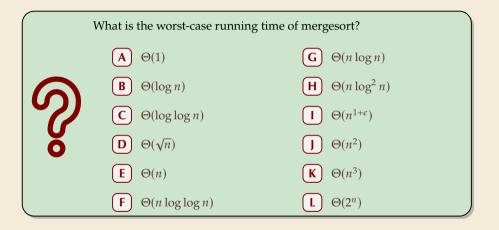


run1

run2

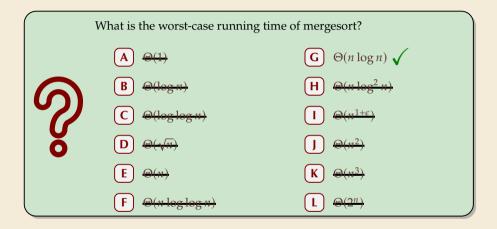
result

Clicker Question



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Clicker Question



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Mergesort

- procedure mergesort(A[l..r))
- $_{2}$ n := r l
- $_3$ if $n \leq 1$ return
- 4 $m := l + \lfloor \frac{n}{2} \rfloor$
- 5 mergesort(A[l..m))
- 6 mergesort(A[m..r))
- 7 merge(A[1..m), A[m..r), buf)
- s copy buf to A[1..r)

- ▶ recursive procedure; *divide & conquer*
- merging needs
 - temporary storage for result of same size as merged runs
 - to read and write each element twice (once for merging, once for copying back)

Mergesort

procedure mergesort(A[l..r))

 $_{2}$ n := r - l

- $_3$ if $n \leq 1$ return
- 4 $m := l + \lfloor \frac{n}{2} \rfloor$
- 5 mergesort(A[l..m))
- 6 mergesort(A[m..r))
- 7 merge(A[l..m), A[m..r), buf)
- s copy buf to A[l..r)

- recursive procedure; divide & conquer
- merging needs
 - temporary storage for result of same size as merged runs
 - to read and write each element twice (once for merging, once for copying back)

Analysis: count "element visits" (read and/or write)

$$C(n) = \begin{cases} 0 & n \le 1 \\ C(\lfloor n/2 \rfloor) + C(\lceil n/2 \rceil) + 2n & n \ge 2 \end{cases}$$
same for best and worst case!

$$k = 2^{k}$$

$$k = 0$$
Simplification $n = 2^{k}$

$$C(2^{k}) = \begin{cases} 0 & k \le 0 \\ 2 \cdot C(2^{k-1}) + 2 \cdot 2^{k} & k \ge 1 \end{cases}$$

$$C(2^{k}) = 2n \lg(n) = \Theta(n \log n)$$

Mergesort – Discussion

 \bigcap optimal time complexity of $\Theta(n \log n)$ in the worst case

stable sorting method i.e., retains relative order of equal-key items

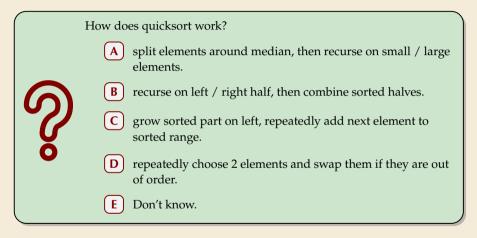
memory access is sequential (scans over arrays)

\square requires $\Theta(n)$ extra space

there are in-place merging methods, but they are substantially more complicated and not (widely) used

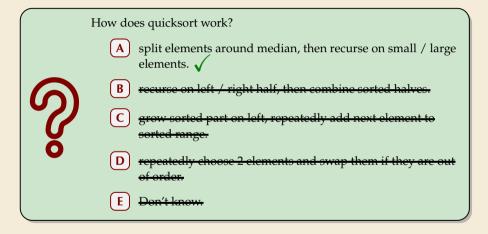
3.2 Quicksort

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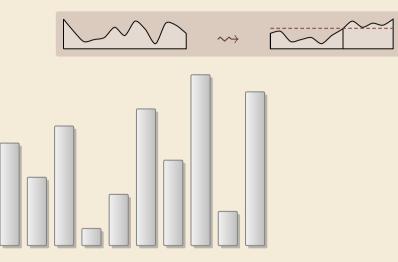


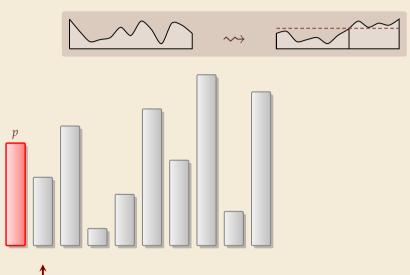
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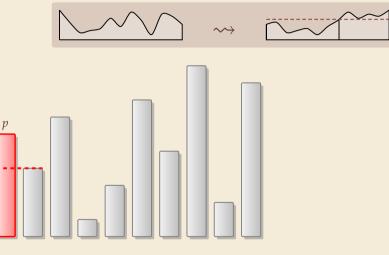


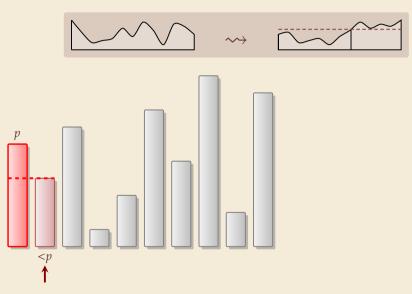
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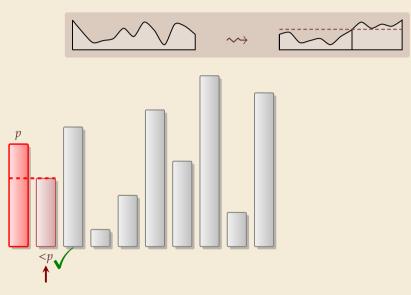


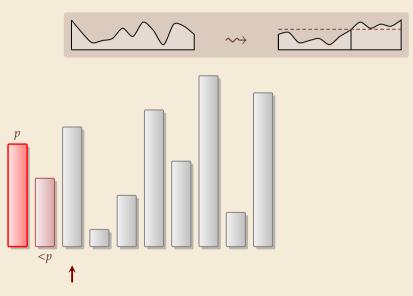


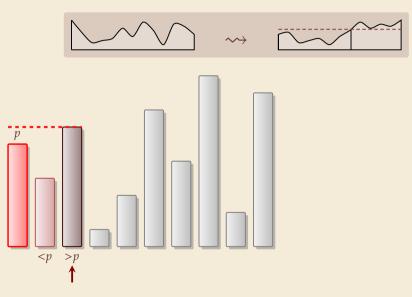
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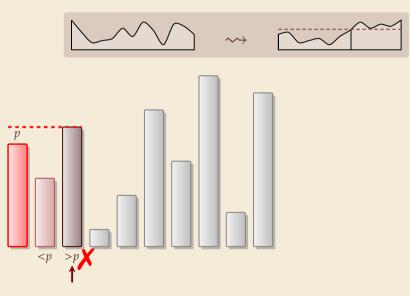


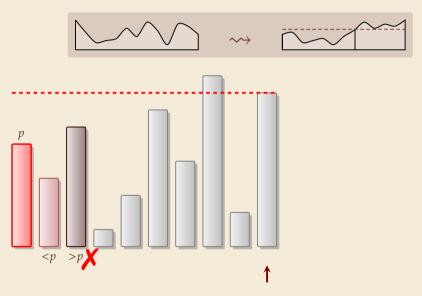


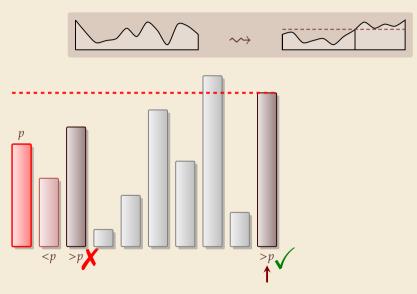


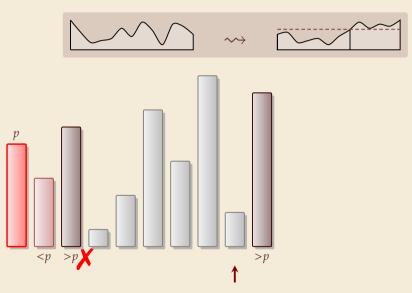


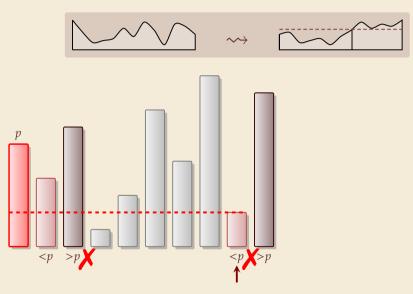


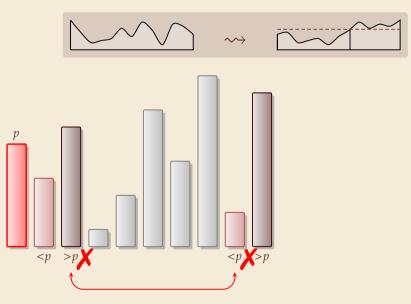


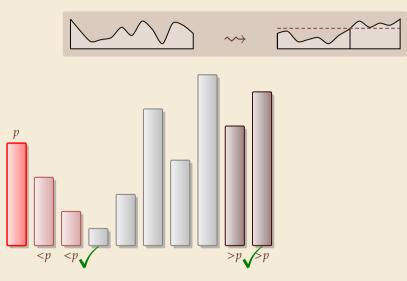


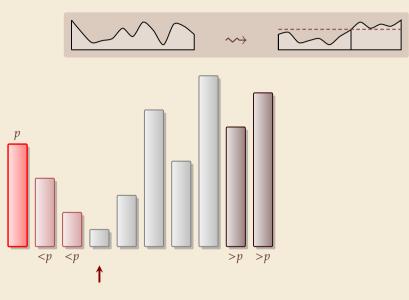


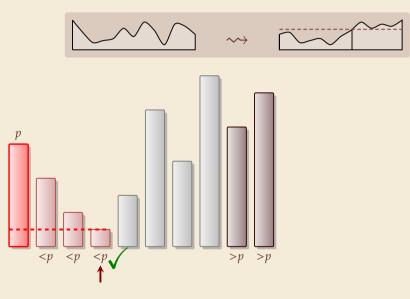


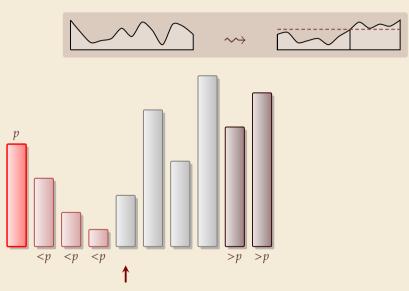


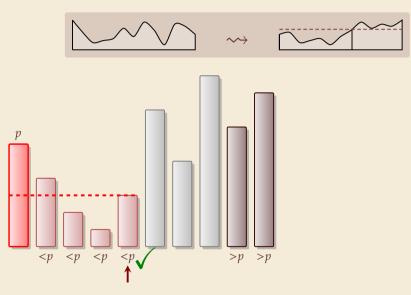


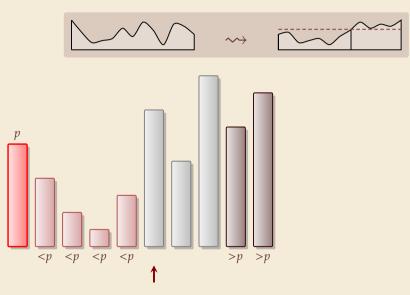


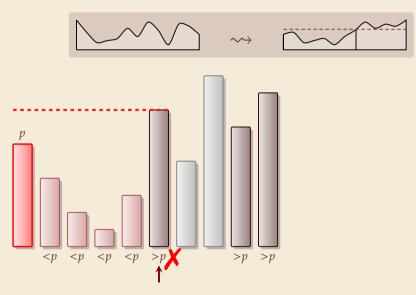


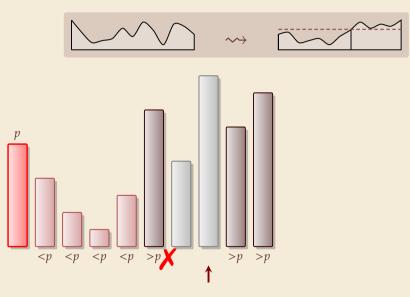


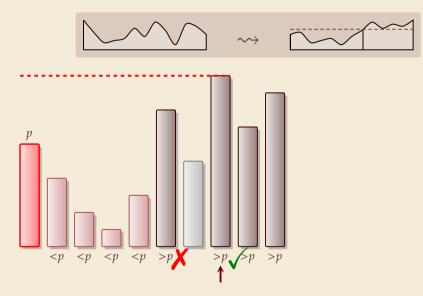


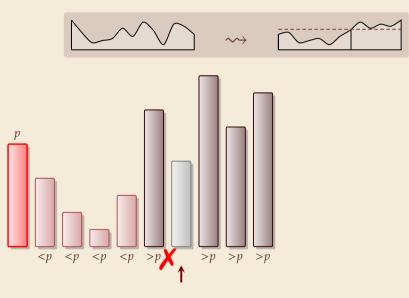


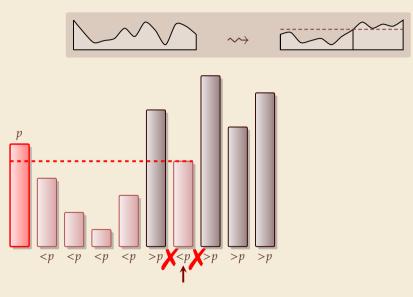


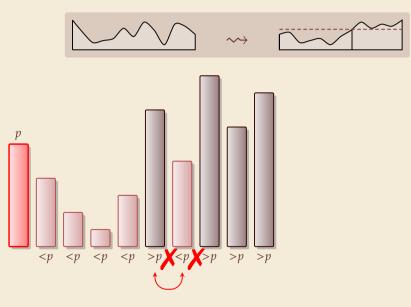


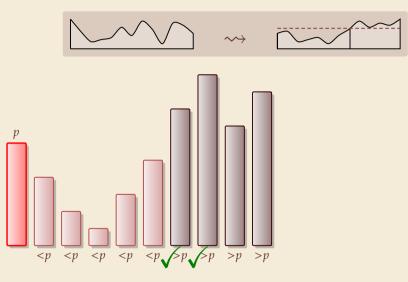


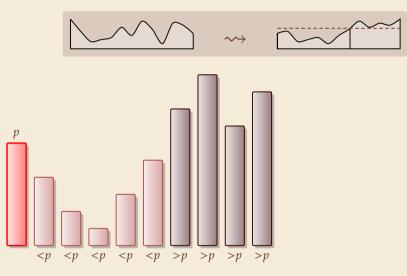


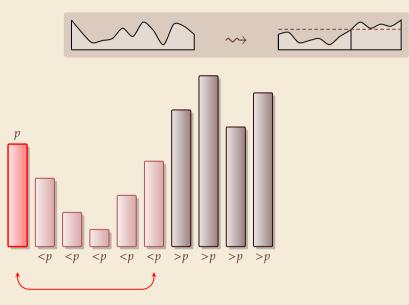


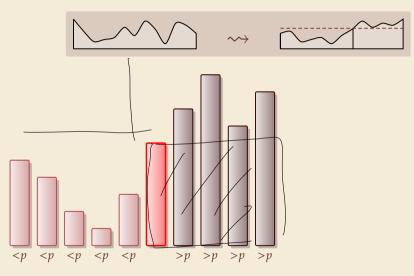


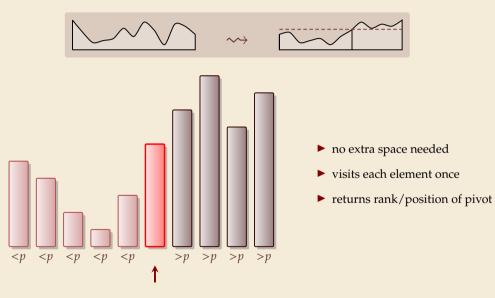












Partitioning – Detailed code

6

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8

9

Beware: details easy to get wrong; use this code!

(if you ever have to)

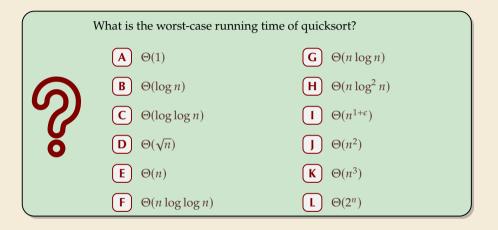
- ¹ **procedure** partition(*A*, *b*)
- ² // input: array A[0..n), position of pivot $b \in [0..n)$
- ³ swap(A[0], A[b])
- $_{4}$ i := 0, j := n
- 5 while true do
 - **do** i := i + 1 **while** i < n and A[i] < A[0]
 - **do** j := j 1 **while** $j \ge 1$ and A[j] > A[0]
 - if $i \ge j$ then break (goto 11)
 - **else** swap(*A*[*i*], *A*[*j*])
- 10 end while
- ¹¹ **swap**(A[0], A[j])
- 12 return j

Loop invariant (5–10): A
$$p \leq p$$
 ? $\geq p$
 i j

- procedure quicksort(A[l..r))
- ² if $r \ell \leq 1$ then return
- b := choosePivot(A[l..r))
- $_{4}$ j := partition(A[l..r), b)
- ⁵ quicksort(A[l..j))
- ⁶ quicksort(A[j+1..r))

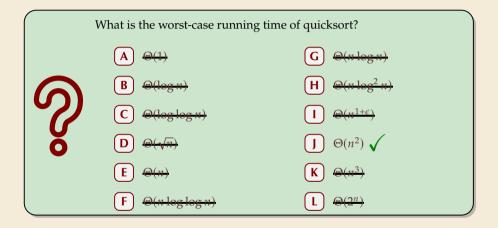
- recursive procedure; divide & conquer
- choice of pivot can be
 - ▶ fixed position → dangerous!
 - random
 - more sophisticated, e.g., median of 3

Clicker Question



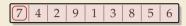
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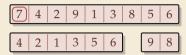
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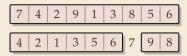


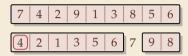
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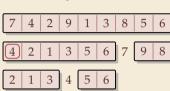
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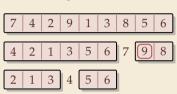


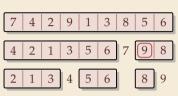


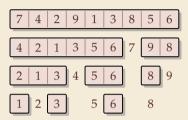


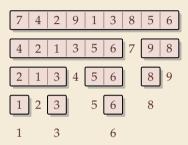


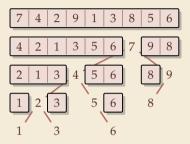


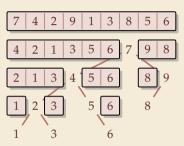




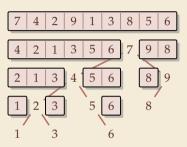




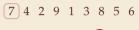




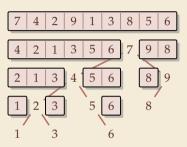
Quicksort



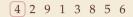
Quicksort



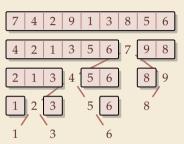




Quicksort



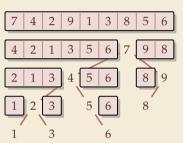




Quicksort





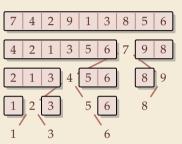


Quicksort

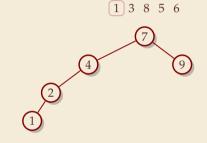
Binary Search Tree (BST)

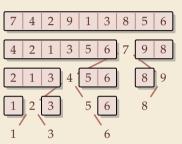
9 1 3 8 5 6



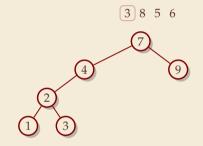


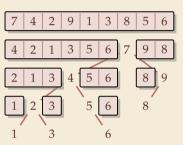
Quicksort



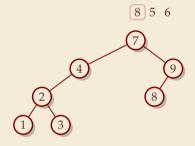


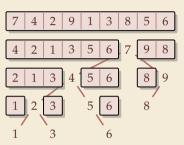
Quicksort



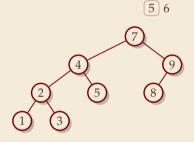


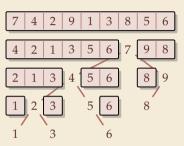
Quicksort



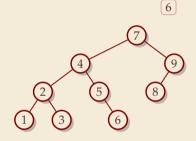


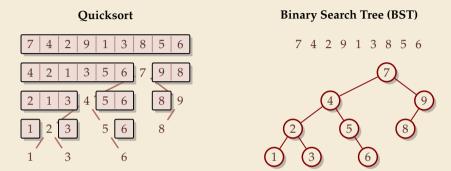
Quicksort





Quicksort





recursion tree of quicksort = binary search tree from successive insertion

- comparisons in quicksort = comparisons to built BST
- comparisons in quicksort \approx comparisons to search each element in BST

Quicksort – Worst Case

▶ Problem: BSTs can degenerate

• Cost to search for k is k - 1

$$\rightarrow$$
 Total cost $\sum_{k=1}^{n} (k-1) = \frac{n(n-1)}{2} \sim \frac{1}{2}n^2$

 \rightsquigarrow quicksort worst-case running time is in $\Theta(n^2)$

terribly slow!

But, we can fix this:

Randomized quicksort:

- choose a *random pivot* in each step
- → same as randomly *shuffling* input before sorting

Randomized Quicksort – Analysis

- ► *C*(*n*) = element visits (as for mergesort)
- \rightsquigarrow quicksort needs $\sim 2 \ln(2) \cdot n \lg n \approx 1.39n \lg n$ in expectation

also: very unlikely to be much worse:
 e.g., one can prove: Pr[cost > 10n lg n] = O(n^{-2.5})
 distribution of costs is "concentrated around mean"

▶ intuition: have to be *constantly* unlucky with pivot choice

Quicksort – Discussion

fastest general-purpose method

 $\Theta(n \log n)$ average case

works *in-place* (no extra space required)

memory access is sequential (scans over arrays)

 $\mathbf{\nabla} \ \Theta(n^2)$ worst case (although extremely unlikely)

not a *stable* sorting method

Open problem: Simple algorithm that is fast, stable and in-place.

3.3 Comparison-Based Lower Bound

Lower Bounds

- **• Lower bound:** mathematical proof that *no algorithm* can do better.
 - very powerful concept: bulletproof *impossibility* result
 - \approx conservation of energy in physics
 - (unique?) feature of computer science:

for many problems, solutions are known that (asymptotically) achieve the lower bound

→ can speak of "*optimal* algorithms"

Lower Bounds

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 - very powerful concept: bulletproof *impossibility* result
 - \approx conservation of energy in physics
 - (unique?) feature of computer science: for many problems, solutions are known that (asymptotically) achieve the lower bound
 can speak of *"optimal* algorithms"
- ▶ To prove a statement about *all algorithms*, we must precisely define what that is!
- already know one option: the word-RAM model
- ▶ Here: use a simpler, more restricted model.

The Comparison Model

- ▶ In the *comparison model* data can only be accessed in two ways:
 - comparing two elements
 - moving elements around (e.g. copying, swapping)
 - ► Cost: number of these operations.

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That's good! /Keeps algorithms general!

- This makes very few assumptions on the kind of objects we are sorting.
- Mergesort and Quicksort work in the comparison model.

The Comparison Model

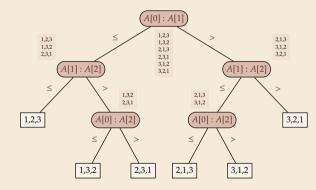
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That's good! 'Keeps algorithms general!

- This makes very few assumptions on the kind of objects we are sorting.
- Mergesort and Quicksort work in the comparison model.
- ---> Every comparison-based sorting algorithm corresponds to a *decision tree*.
 - ▶ only model comparisons → ignore data movement
 - nodes = comparisons the algorithm does
 - next comparisons can depend on outcomes ~>> different subtrees
 - child links = outcomes of comparison
 - leaf = unique initial input permutation compatible with comparison outcomes

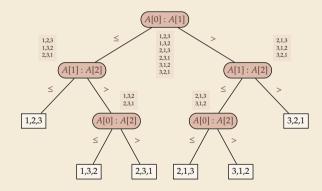
Comparison Lower Bound

Example: Comparison tree for a sorting method for *A*[0..2]:



Comparison Lower Bound

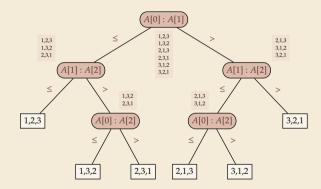
Example: Comparison tree for a sorting method for *A*[0..2]:



- Execution = follow a path in comparison tree.
- worst-case # comparisons
- comparison trees are *binary* trees
- $\rightsquigarrow \ \ell \ \text{leaves} \ \rightsquigarrow \ \text{height} \geq \lceil \lg(\ell) \rceil$
- ▶ comparison trees for sorting method must have ≥ n! leaves
- $\label{eq:height} \begin{array}{l} \rightsquigarrow \quad \text{height} \geq \lg(n!) \sim n \lg n \\ \\ \text{more precisely: } \lg(n!) \stackrel{\bigstar}{=} n \lg n \lg(e)n + O(\log n) \end{array}$

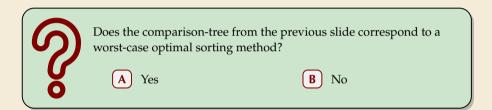
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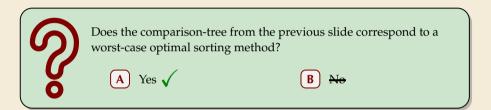
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- ► comparison trees for sorting method must have ≥ n! leaves
- $\rightarrow height \ge \lg(n!) \sim n \lg n$ more precisely: $\lg(n!) = n \lg n - \lg(e)n + O(\log n)$
- Mergesort achieves ~ $n \lg n$ comparisons \rightarrow asymptotically comparison-optimal!
- ▶ Open (theory) problem: Sorting algorithm with $n \lg n \lg(e)n + o(n)$ comparisons?

Clicker Question





Clicker Question





3.4 Integer Sorting

• Does the above lower bound mean, sorting always takes time $\Omega(n \log n)$?

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► Here: sort *n* integers

▶ can do *a lot* with integers: add them up, compute averages, ... (full power of word-RAM)

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- \rightsquigarrow above lower bound does not apply!

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- ▶ can do *a lot* with integers: add them up, compute averages, ... (full power of word-RAM)
- $\rightsquigarrow~$ we are **not** working in the comparison model
- \rightsquigarrow above lower bound does not apply!
- ▶ but: a priori unclear how much arithmetic helps for sorting ...

Counting sort

- Important parameter: size/range of numbers
 - ▶ numbers in range $[0..U) = \{0, ..., U 1\}$ typically $U = 2^b \iff b$ -bit binary numbers

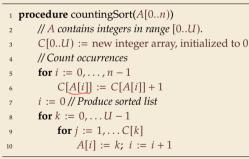
Counting sort

Important parameter: size/range of numbers

▶ numbers in range $[0..U) = \{0, ..., U - 1\}$ typically $U = 2^b \iff b$ -bit binary numbers

• We can sort *n* integers in $\Theta(n + U)$ time and $\Theta(U)$ space when $b \le w$:

Counting sort



count how often each *possible* value occurs

word size

- produce sorted result directly from counts
- circumvents lower bound by using integers as array index / pointer offset

 \rightsquigarrow Can sort *n* integers in range [0..*U*) with U = O(n) in time and space $\Theta(n)$.

Integer Sorting – State of the art

- O(n) time sorting also possible for numbers in range $U = O(n^c)$ for constant *c*.
 - *radix sort* with radix 2^w

Algorithm theory

- suppose $U = 2^w$, but w can be an arbitrary function of n
- how fast can we sort n such w-bit integers on a w-bit word-RAM?
 - for $w = O(\log n)$: linear time (*radix/counting sort*)
 - for $w = \Omega(\log^{2+\varepsilon} n)$: linear time (signature sort)
 - ► for *w* in between: can do $O(n\sqrt{\lg \lg n})$ (very complicated algorithm) don't know if that is best possible!

& exam

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* * *

▶ for the rest of this unit: back to the comparisons model!

Part II Exploiting presortedness

3.5 Adaptive Sorting

Adaptive sorting

- ► Comparison lower bound also holds for the *average case* $\rightarrow \lfloor \lg(n!) \rfloor$ cmps necessary
- Mergesort and Quicksort from above use $\sim n \lg n$ cmps even in best case

Adaptive sorting

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Can we do better if the input is already "almost sorted"?

Scenarios where this may arise naturally:

- Append new data as it arrives, regularly sort entire list (e.g., log files, database tables)
- Compute summary statistics of time series of measurements that change slowly over time (e. g., weather data)
- Merging locally sorted data from different servers (e.g., map-reduce frameworks)
- → Ideally, algorithms should *adapt* to input: *the more sorted the input, the faster the algorithm* ... but how to do that!?

Warmup: check for sorted inputs

- Any method could first check if input already completely in order!
 - Best case becomes $\Theta(n)$ with n 1 comparisons!
 - \bigcirc Usually n 1 extra comparisons and pass over data "wasted"
 - Only catches a single, extremely special case . . .

Warmup: check for sorted inputs

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- ► For divide & conquer algorithms, could check in each recursive call!
 - Potentially exploits partial sortedness!
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For Mergesort, can instead check before merge with a **single** comparison

► If last element of first run ≤ first element of second run, skip merge

How effective is this idea?

1procedure mergesortCheck(A[l..r))2n := r - l3if $n \le 1$ return4 $m := l + \lfloor \frac{n}{2} \rfloor$ 5mergesortCheck(A[l..m))6mergesortCheck(A[m..r))7if A[m-1] > A[m]8merge(A[l..m), A[m..r), buf)9copy buf to A[l..r)

- Simplified cost measure: <u>merge cost</u> = size of output of merges
 - \approx number of comparisons
 - \approx number of memory transfers / cache misses

Example input: n = 64 numbers in sorted *runs* of 16 numbers each:



Simplified cost measure: merge cost = size of output of merges

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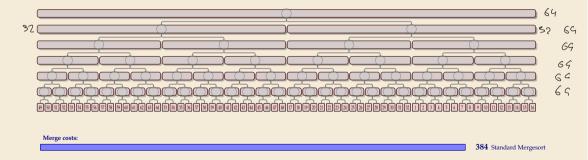
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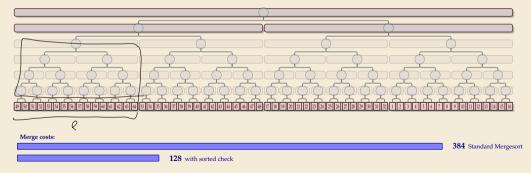
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Simplified cost measure: merge cost = size of output of merges

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Example input: n = 64 numbers in sorted *runs* of 16 numbers each:



Sorted check can help a lot!

Alignment issues

• In previous example, each run of length ℓ saved us $\ell \lg(\ell)$ in merge cost.

- = exactly the cost of *creating* this run in mergesort had it not already existed

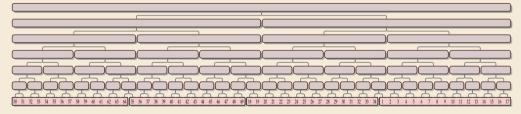
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- $\rightsquigarrow\,$ best savings we can hope for!
- \rightsquigarrow Are overall merge costs $\mathcal{H}(\ell_1, \ldots, \ell_r) := n \lg(n) -$

$$\underbrace{g(n)}_{\text{gesort}} - \underbrace{\sum_{i=1}^{r} \ell_i^{\ell_i = \text{length of } i\text{th run}}}_{i = 1} \underbrace{f_i^{\ell_i} \log(\ell_i) ?}$$

savings from runs



mei

Merge costs:

384 Standard Mergesort

Unfortunately, not quite:

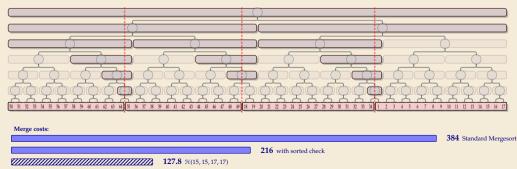
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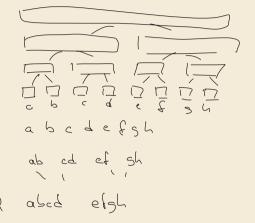
mer

Unfortunately, not quite:

Natural Bottom-Up Mergesort

• Can we do better by explicitly detecting runs?

| 1 | procedure bottomUpMergesort(<i>A</i> [0 <i>n</i>)) | |
|----|---|---|
| 2 | <i>Q</i> := new Queue // runs to merge | |
| 3 | // Phase 1: Enqueue singleton runs | |
| 4 | for $i = 0,, n - 1$ do | |
| 5 | Q.enqueue((i, i)) | |
| 6 | // Phase 2: Merge runs level–wise | |
| 7 | while $\neg Q.isEmpty()$ | |
| 8 | Q' := new Queue | G |
| 9 | while $Q.size() \ge 2$ | Q |
| 10 | $(i_1, j_1) := Q.dequeue()$ | 6 |
| 11 | $(i_2, j_2) := Q.dequeue()$ | C |
| 12 | merge($A[i_1j_1], A[i_2j_2], buf$) | |
| 13 | copy <i>buf</i> to $A[i_1j_2]$ | C |
| 14 | Q' .enqueue $((i_1, j_2))$ | |
| 15 | if $\neg Q.isEmpty()$ | |
| 16 | Q'.enqueue(Q .dequeue()) | |
| 17 | Q := Q' | |



Natural Bottom-Up Mergesort

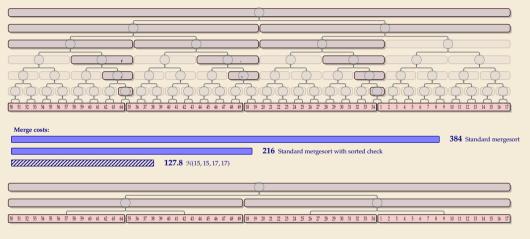
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| 15 | if $\neg Q.isEmpty()$ |
| 16 | Q'.enqueue $(Q$.dequeue $())$ |
| 17 | Q := Q' |

| 1 | procedure naturalMergesort(A[0n)) |
|----|--|
| 2 | Q := new Queue; $i := 0$ find run (i, j) |
| 3 | for $i < n$ do |
| 4 | j := i |
| 5 | while $A[j+1] \ge A[j]$ do $j := j+1$ |
| 6 | Q.enqueue((i, j)); i := j + 1 |
| 7 | while $\neg Q.isEmpty()$ |
| 8 | Q' := new Queue |
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Natural Bottom-Up Mergesort – Analysis

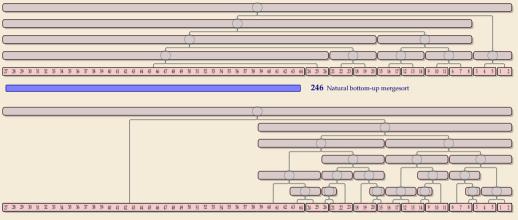
▶ Works well runs of roughly equal size, regardless of alignment ...



128 Natural bottom-up mergesort

Natural Bottom-Up Mergesort – Analysis [2]

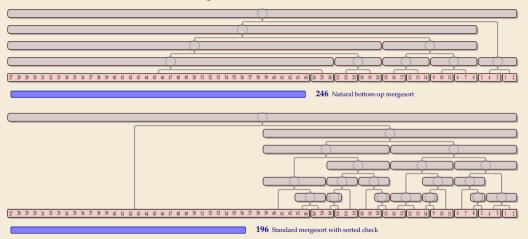
▶ ... but less so for uneven run lengths



196 Standard mergesort with sorted check

Natural Bottom-Up Mergesort – Analysis [2]

▶ ... but less so for uneven run lengths



... can't we have both at the same time?!

Let's take a step back and breathe.

Let's take a step back and breathe.

- Conceptually, there are two tasks:
 - **1.** Detect and use existing runs in the input $\rightsquigarrow \ell_1, \ldots, \ell_r$ (easy)
 - 2. Determine a favorable *order of merges* of runs

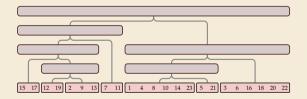
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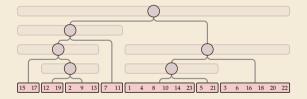
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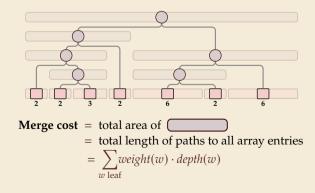
= total length of paths to all array entries

Good merge orders

Let's take a step back and breathe.

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("automatic" in top-down mergesort)



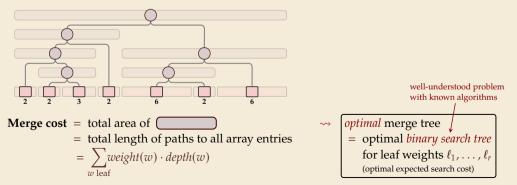
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$$\ell_r$$
 (easy)

("automatic" in top-down mergesort)



Nearly-Optimal Mergesort

Nearly-Optimal Mergesorts: Fast, Practical Sorting Methods That Optimally Adapt to Existing Runs

J. Ian Munro University of Waterloo, Canada Internet/Interaterloo.ca @ https://cecid.org/0000-0002-7165-7988

Sebastian Wild University of Waterloo, Canada wild/investerios.ca https://oceid.org/0000-0002-6061-9172

____ Abstract

We present two stable mergener variants, "produced" and "powersent", that applied residing range and find analy-spring management of the applied resident. Pervison methods there respire a solution of the respire of the stable of the respire of the respi

2012 ACM Subject Classification Theory of computation -> Sorting and searching

Keywords and phrases adaptive sorting, nearly-optimal binary search trees, Timsort

Digital Object Identifier 10.4230/LIPIcs.ESA.2018.63

Related Version arXiv: 1805.04154 (extended version with appendices)

Supplement Material zenodo: 1241162 (code to reproduce running time study)

Funding This work was supported by the Natural Sciences and Engineering Research Council of Canada and the Canada Research Chairs Programme.

1 Introduction

Sorting is a fundamental hudding black for sumerous tasks and subspirates in both the theory and practice of computing. While practical and theoretically (close-to) optimal comparison-based serting methods are known, instance-optimal zerting, i.e., methods that adapt to the actual input and exploit specific structural properties if present, is still an area of active research. We survey some second development in Section 1.1.

Many different structural properties have been investigated in theory. Two of them have also found wide adoption is presenter, α_{ij} in Order's Jones mutual Haver, studging to the presence of duplicate keys and using existing sorted segments, called reast. The former is ableved by a so-califord for going partitioning sciential of galaxies [16] width a data sould in the OpenRiSD implementation of appear from the C standard Binesy. It is an associate action the presence, it is however used in Java and Mark for gratinitive spin servers.

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- In 2018, with Ian Munro, I combined research on nearly-optimal BSTs with mergesort
- → 2 new algorithms: *Peeksort* and *Powersort*

both adapt provably optimal to existing runs even in worst case: mergecost ≤ H(l₁,..., l_r) + 2n

- both are lightweight extensions of existing methods with negligible overhead
- both fast in practice

- based on top-down mergesort
- "peek" at middle of array & find closest run boundary





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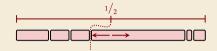
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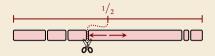
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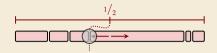
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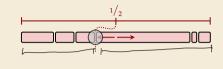
- based on top-down mergesort
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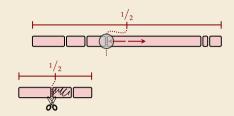


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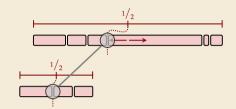




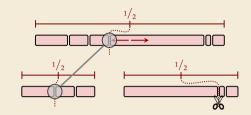
- based on top-down mergesort
- "peek" at middle of array & find closest run boundary
- → split there and recurse (instead of at midpoint)



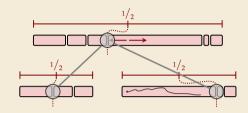
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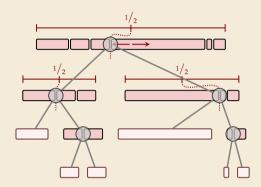
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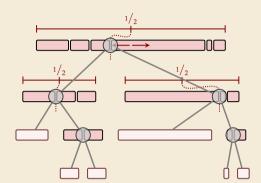


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& exan

- based on top-down mergesort
- "peek" at middle of array & find closest run boundary
- → split there and recurse (instead of at midpoint)



- can avoid scanning runs repeatedly:
 - find full run straddling midpoint
 - remember length of known runs at boundaries



 $\rightsquigarrow~$ with clever recursion, scan each run only once.

Peeksort – Code

procedure peeksort($A[\ell..r), \Delta_{\ell}, \Delta_{r}$) if $r - \ell < 1$ then return 2 if $\ell + \Delta_{\ell} == r \vee \ell == r + \Delta_r$ then return 3 $m := \ell + |(r - \ell)/2|$ 4 5 $i := \begin{cases} \ell + \Delta_{\ell} & \text{if } \ell + \Delta_{\ell} \ge m \\ \text{extendRunLeft}(A, m) & \text{else} \end{cases}$ 6 $j := \begin{cases} r + \Delta_{r} \le m & \text{if } r + \Delta_{r} \le m \le m \\ \text{extendRunRight}(A, m) & \text{else} \end{cases}$ 7 $g := \begin{cases} i & \text{if } m - i < j - m \\ j & \text{else} \end{cases}$ 8 $\Delta_g := \begin{cases} j - i & \text{if } m - i < j - m \\ i - j & \text{else} \end{cases}$ peeksort($A[\ell..g), \Delta_{\ell}, \Delta_{\varphi}$) 9 peeksort($A[g, r), \Delta_{\sigma}, \Delta_{r}$) 10 $merge(A[\ell, g), A[g..r), buf)$ 11 copy *buf* to $A[\ell..r)$

► Parameters:



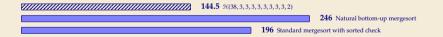
- initial call: peeksort($A[0..n), \Delta_0, \Delta_n$) with Δ_0 = extendRunRight(A, 0) $\Delta_n = n$ - extendRunLeft(A, n)
- helper procedure

1 procedure extendRunRight(A[0..n), i) 2 j := i + 13 while $j < n \land A[j - 1] \le A[j]$ 4 j := j + 15 return j

(extendRunLeft similar)

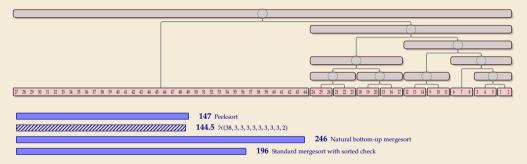
Peeksort – Analysis

• Consider tricky input from before again:



Peeksort – Analysis

Consider tricky input from before again:



- One can prove: Mergecost always $\leq \mathfrak{H}(\ell_1, \ldots, \ell_r) + 2n$
- \rightsquigarrow We can have the best of both worlds!

3.6 Python's list sort

Sorting in Python

- ► CPython
 - *Python* is only a specification of a programming language
 - The Python Foundation maintains *CPython* as the official reference implementation of the Python programming language
 - If you don't specifically install something else, python will be CPython
- part of Python are list.sort resp. sorted built-in functions
 - implemented in C
 - use *Timsort*, custom Mergesort variant by Tim Peters

Sorting in Python

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Sept 2021: **Python uses** *Powersort*! in CPython 3.11 and PyPy 7.3.6

| msg400864 - Author: Tim Peters (tim. (view) | Date peters) * 🏓 2021-09-0. 19:4: |
|---|--|
| I created a PR that implements the powersort | merge strategy: |
| https://github.com/python/cpython/pull/28108 | |
| Across all the time this issue report has bee to be the top contender. Enough already :-> 1 change to make to the code, but that's in rel it's not at all a hard change. | It's indeed a more difficult |
| Laurent, if you find that some variant of Shi than that, let us know here! I'm a big fan of powersort seens to do somewhat better 'on ave adaptive ShiversSort (and implementing that to outside of merge_collaps()). | f Vincent's innovations too, but erage" than even his length- |

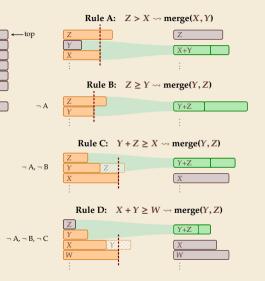
Timsort (original version)

runs

Y X W

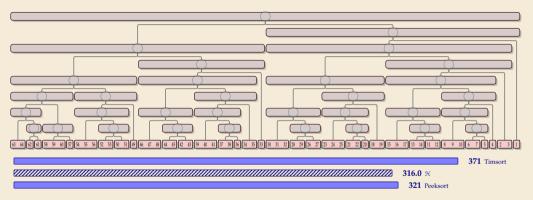
| <pre>procedure Timsort(A[0n))</pre> | |
|-------------------------------------|-------------------------------|
| 2 | i := 0; runs := new Stack() |
| 3 | while $i < n$ |
| 4 | j := ExtendRunRight(A, i) |
| 5 | runs.push(i, j); i := j |
| 6 | while rule A/B/C/D applicable |
| 7 | merge corresponding runs |
| 8 | while $runs.size() \ge 2$ |
| 9 | merge topmost 2 runs |

- above shows the core algorithm; many more algorithm engineering tricks
- Advantages:
 - profits from existing runs
 - locality of reference for merges
- But: not optimally adaptive! (next slide) Reason: Rules A–D (Why exactly these?!)



Timsort bad case

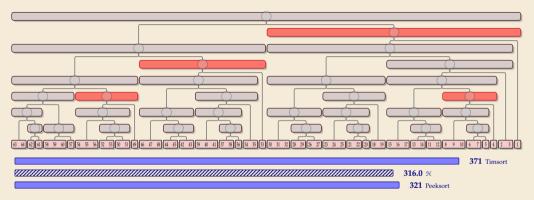
• On certain inputs, Timsort's merge rules don't work well:



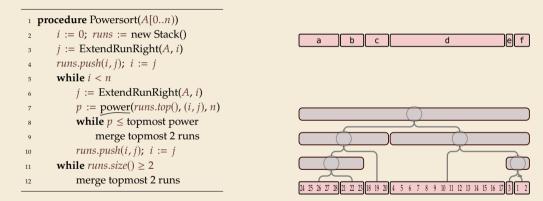
► As *n* increases, Timsort's cost approach 1.5 · H, i. e., 50% more merge costs than necessary

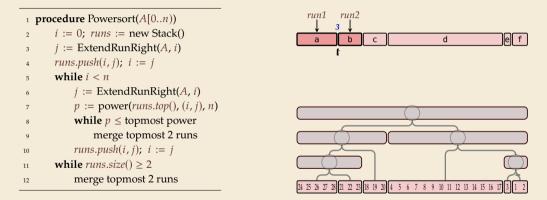
Timsort bad case

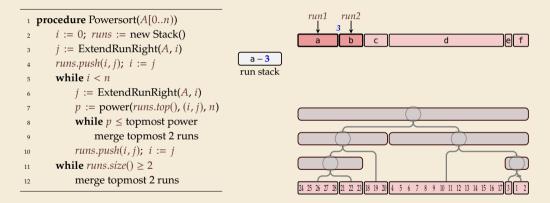
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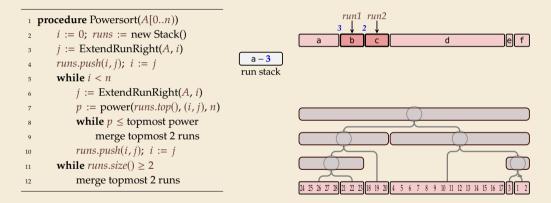


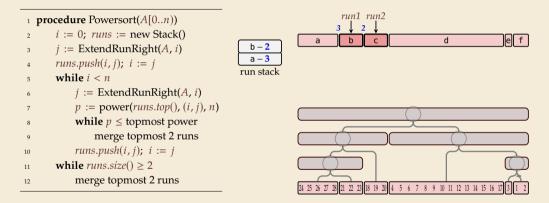
- ▶ As *n* increases, Timsort's cost approach $1.5 \cdot H$, i. e., 50% more merge costs than necessary
 - intuitive problem: regularly very unbalanced merges

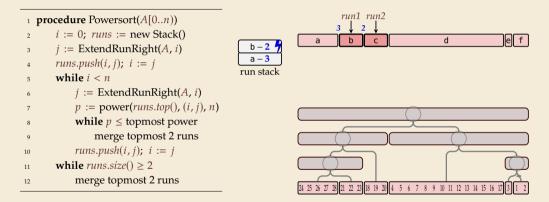


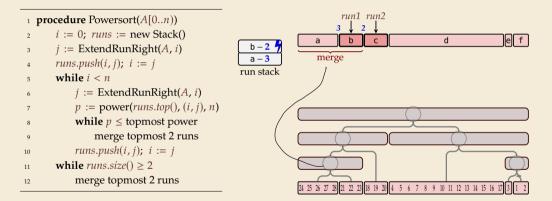


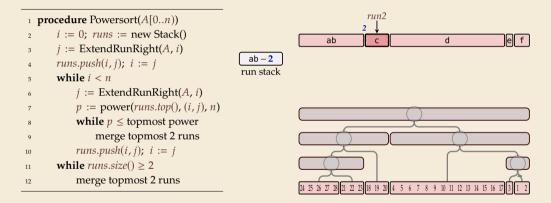


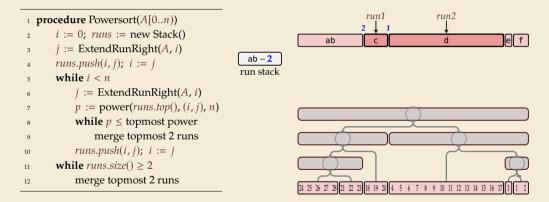


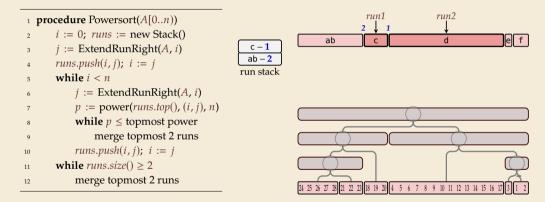


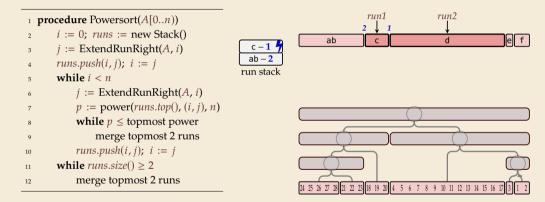


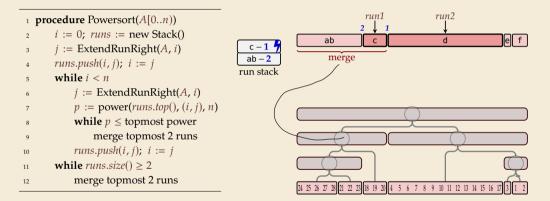


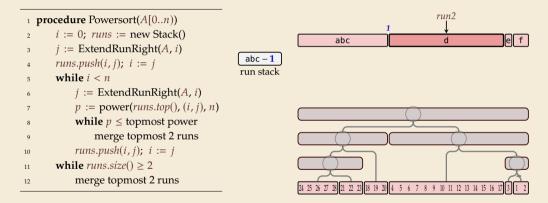


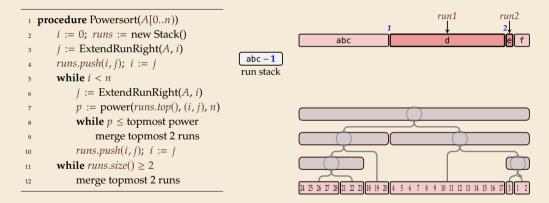


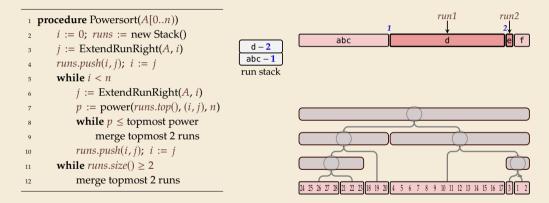


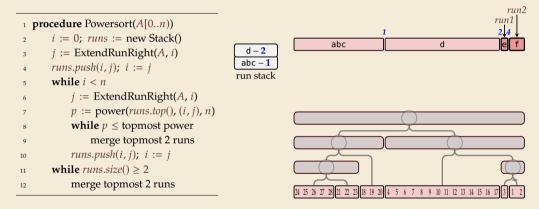


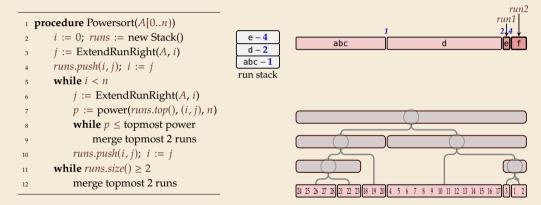


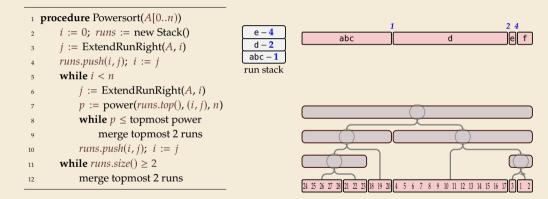


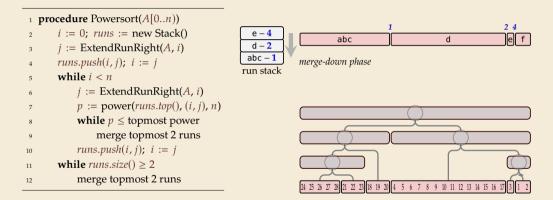


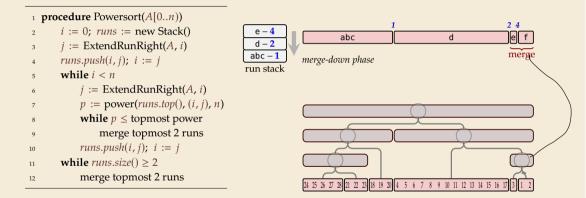


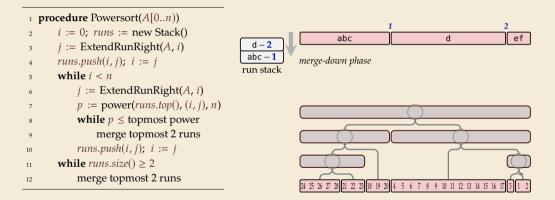


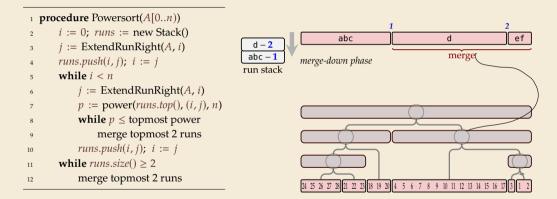


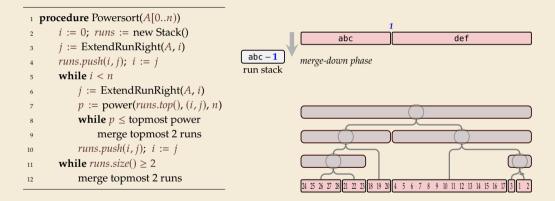


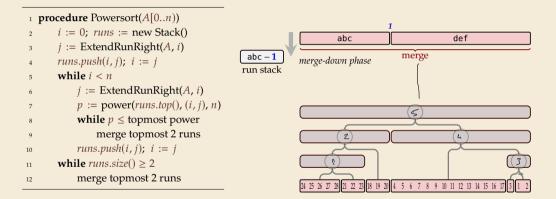


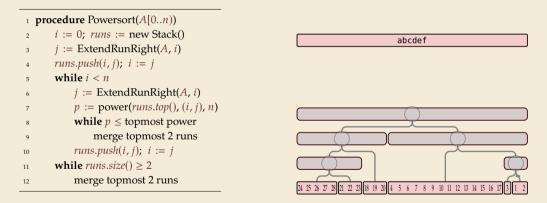










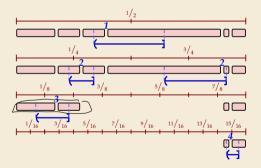


Powersort – Computing powers

• Computing the power of (the node between) two runs $A[i_1..j_1]$ and $A[i_2..j_2]$

 ► (-] = normalized midpoint interval
 ▶ power = min ℓ s.t. (-) contains c ⋅ 2^{-ℓ}

¹ **procedure** power($(i_1, j_1), (i_2, j_2), n$) $n_1 := i_1 - i_1 + 1$ 2 $n_2 := i_2 - i_2 + 1$ 3 $a := \frac{i_1 + \frac{1}{2}n_1 - 1}{1 - 1}$ 4 $b := \frac{i_2 + \frac{1}{2}n_2 - 1}{2}$ ____ // interval (a, b] 5 $\ell := 0$ 6 while $|a \cdot 2^{\ell}| = |b \cdot 2^{\ell}|$ 7 $\ell := \ell + 1$ 8 return ℓ 0

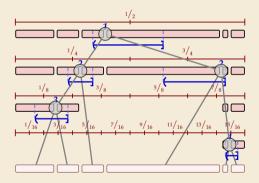


Powersort – Computing powers

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 ► ←] = normalized midpoint interval
 ▶ power = min ℓ s.t. ←] contains c ⋅ 2^{-ℓ}

procedure power((*i*₁, *j*₁), (*i*₂, *j*₂), *n*) $n_1 := i_1 - i_1 + 1$ 2 $n_2 := i_2 - i_2 + 1$ 3 $a := \frac{i_1 + \frac{1}{2}n_1 - 1}{1 - 1}$ 4 $b := \frac{i_2 + \frac{1}{2}n_2 - 1}{n_2 - 1} // interval(a, b)$ 5 $\ell := 0$ 6 while $|a \cdot 2^{\ell}| = |b \cdot 2^{\ell}|$ 7 $\ell := \ell + 1$ 8 return ℓ 0

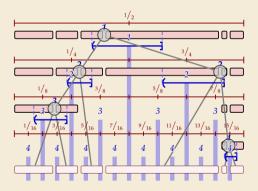


Powersort – Computing powers

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Powersort – Discussion

Retains all advantages of Timsort

- good locality in memory accesses
- no recursion
- all the tricks in Timsort

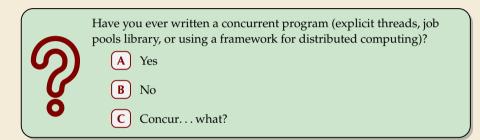
optimally adapts to existing runs
 minimal overhead for finding merge order

35 & 36 & exam

Part III Sorting with of many processors

3.7 Parallel computation

Clicker Question





Types of parallel computation

 $\pounds\pounds\pounds$ can't buy you more time . . . but more computers!

→ Challenge: Algorithms for *parallel* computation.

Types of parallel computation

£££ can't buy you more time ... but more computers! ~ Challenge: Algorithms for *parallel* computation.

There are two main forms of parallelism:

- **1.** shared-memory parallel computer \leftarrow focus of today \bigcirc_{per}
 - ▶ *p processing elements* (PEs, processors) working in parallel
 - single big memory, accessible from every PE
 - communication via shared memory
 - ▶ think: a big server, 128 CPU cores, terabyte of main memory
- 2. distributed computing MPT
 - ▶ *p* PEs working in parallel
 - each PE has private memory
 - communication by sending messages via a network
 - think: a cluster of individual machines

Open MP, Jov. threads C++ Python

PRAM – Parallel RAM

extension of the RAM model (recall Unit 1)

- the *p* PEs are identified by ids $0, \ldots, p-1$
 - like w (the word size), p is a parameter of the model that can grow with n
 - $p = \Theta(n)$ is not unusual maaany processors!
- the PEs all independently run & RAM-style program (they can use their id there)
- ▶ each PE has its own registers, but MEM is shared among all PEs
- computation runs in synchronous steps: in each time step, every PE executes one instruction

PRAM – Conflict management

Problem: What if several PEs simultaneously overwrite a memory cell?

- EREW-PRAM (exclusive read, exclusive write) any parallel access to same memory cell is forbidden (cra
- CREW-PRAM (concurrent read, exclusive write) parallel write access to same memory cell is *forbidden*, but reading is fine
- CRCW-PRAM (concurrent read, concurrent write) concurrent access is allowed, need a rule for write conflicts:
 - common CRCW-PRAM: all concurrent writes to same cell must write same value
 - arbitrary CRCW-PRAM: some unspecified concurrent write wins
 - (more exist . . .)

no single model is always adequate, but our default is CREW





(crash if happens)

PRAM – Execution costs

Cost metrics in PRAMs

- **space:** total amount of accessed memory
- time: number of steps till all PEs finish sometimes called *depth* or *span*
- ▶ work: total #instructions executed on all PEs

assuming sufficiently many PEs!

PRAM – Execution costs

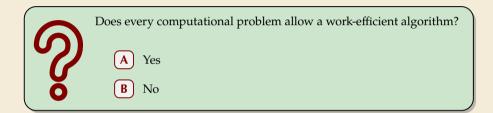
Cost metrics in PRAMs

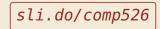
- space: total amount of accessed memory
- time: number of steps till all PEs finish sometimes called *depth* or *span*assuming sufficiently many PEs!
- ▶ work: total #instructions executed on all PEs

Holy grail of PRAM algorithms:

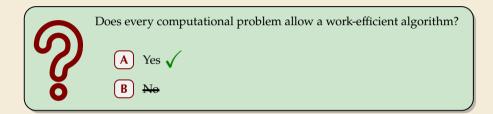
- minimal time
- work (asymptotically) no worse than running time of best sequential algorithm
 "work-efficient" algorithm: work in same Θ-class as best sequential

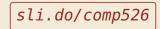
Clicker Question





Clicker Question





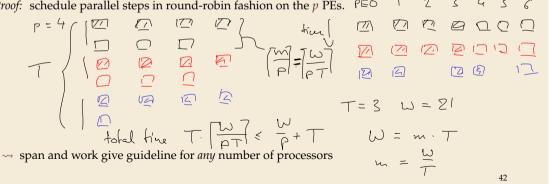
The number of processors

Hold on, my computer does not have $\Theta(n)$ processors! Why should I care for span and work!?

Theorem 3.1 (Brent's Theorem:)

If an algorithm has span T and work W (for an arbitrarily large number of processors), it can be run on a PRAM with *p* PEs in time $O(T + \frac{W}{p})$ (and using O(W) work). MPF

PEO 1 2 3 4 5 6 *Proof:* schedule parallel steps in round-robin fashion on the *p* PEs.



3.8 Parallel primitives

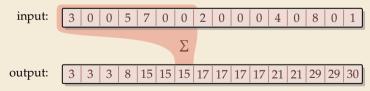
Prefix sums

Before we come to parallel sorting, we study some useful building blocks.

Prefix-sum problem (also: cumulative sums, running totals)

- Given: array A[0..n) of numbers
- ► Goal: compute all prefix sums A[0] + · · · + A[i] for i = 0, . . . , n − 1 may be done "in-place", i. e., by overwriting A

Example:



Clicker Question





Clicker Question





Prefix sums – Sequential

- sequential solution does n 1 additions
- but: cannot parallelize them!data dependencies!
- \rightsquigarrow need a different approach

procedure prefixSum(A[0..n))

for
$$i := 1, ..., n - 1$$
 do

$$A[i] := A[i-1] + A[i]$$

Prefix sums – Sequential

- sequential solution does n 1 additions
- but: cannot parallelize them!data dependencies!
- → need a different approach

Let's try a simpler problem first.

Excursion: Sum

- ▶ Given: array *A*[0..*n*) of numbers
- ► Goal: compute A[0] + A[1] + · · · + A[n 1] (solved by prefix sums)

1 **procedure** prefixSum(A[0..n)) 2 **for** i := 1, ..., n - 1 **do** 3 A[i] := A[i-1] + A[i]

Prefix sums – Sequential

- sequential solution does n 1 additions
- but: cannot parallelize them!
 data dependencies!
- → need a different approach
- Let's try a simpler problem first.

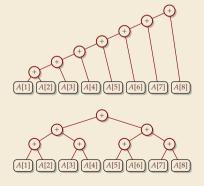
Excursion: Sum

- ▶ Given: array *A*[0..*n*) of numbers
- ► Goal: compute A[0] + A[1] + · · · + A[n 1] (solved by prefix sums)

Any algorithm *must* do n - 1 binary additions

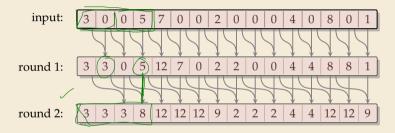
 \rightarrow Height of tree = parallel time!

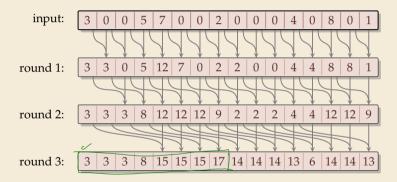
- ¹ **procedure** prefixSum(A[0..n)) ² **for** i := 1, ..., n - 1 **do**
- A[i] := A[i-1] + A[i]

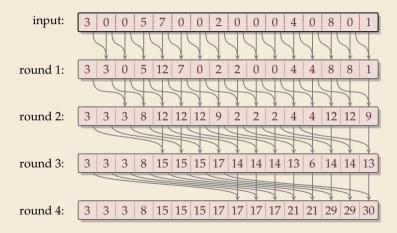


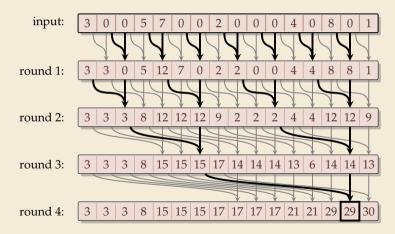












Parallel prefix sums – Code

can be realized in-place (overwriting A)

▶ assumption: in each parallel step, all reads precede all writes

Span
i procedure parallelPrefixSums(
$$A[0.n)$$
)
i procedure parallelPrefixSums($A[0.n)$)
i procedure parallelPrefixSums($A[0.n]$)
i procedure parallelPre

Parallel prefix sums – Analysis

► Time:

- all additions of one round run in parallel
- ▶ $\lceil \lg n \rceil$ rounds
- $\rightsquigarrow \Theta(\log n)$ time best possible!

► Work:

- ▶ $\geq \frac{n}{2}$ additions in all rounds (except maybe last round)
- $\rightsquigarrow \Theta(n \log n)$ work
- more than the $\Theta(n)$ sequential algorithm!

Parallel prefix sums – Analysis

► Time:

- all additions of one round run in parallel
- \blacktriangleright [lg n] rounds
- $\rightsquigarrow \Theta(\log n)$ time best possible!

► Work:

- $\blacktriangleright \geq \frac{n}{2}$ additions in all rounds (except maybe last round)
- $\rightsquigarrow \Theta(n \log n)$ work
- more than the $\Theta(n)$ sequential algorithm!

► Typical trade-off: greater parallelism at the expense of more overall work

Parallel prefix sums – Analysis

► Time:

- all additions of one round run in parallel
- \blacktriangleright [lg n] rounds
- $\rightsquigarrow \Theta(\log n)$ time best possible!

Work:

- $\blacktriangleright \geq \frac{n}{2}$ additions in all rounds (except maybe last round)
- $\rightsquigarrow \Theta(n \log n)$ work
- more than the $\Theta(n)$ sequential algorithm!
- ▶ Typical trade-off: greater parallelism at the expense of more overall work

For prefix sums:

- can actually get $\Theta(n)$ work in *twice* that time!
- $\rightsquigarrow~$ algorithm is slightly more complicated
- ▶ instead here: linear work in *thrice* the time using "blocking trick"

Work-efficient parallel prefix sums

standard trick to improve work: compute small blocks sequentially

- **1.** Set $b := \lceil \lg n \rceil$
- **2.** For blocks of *b* consecutive indices, i. e., *A*[0..*b*), *A*[*b*..2*b*), . . . do in parallel: compute local prefix sums sequentially
- **3.** Use previous work-inefficient algorithm only on rightmost elements of block, i. e., to compute prefix sums of A[b-1], A[2b-1], A[3b-1], ...
- **4.** For blocks *A*[0..*b*), *A*[*b*..2*b*), . . . do in parallel: Add block-prefix sums to local prefix sums

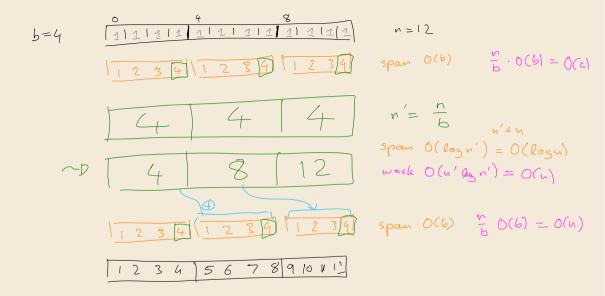
Analysis:

► Time:

- 2. & 4.: $\Theta(b) = \Theta(\log n)$ time
- ► 3. $\Theta(\log(n/b)) = \Theta(\log n)$ times

Work:

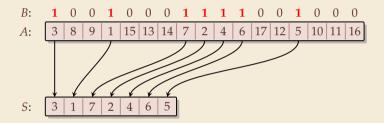
- ▶ 2. & 4.: $\Theta(b)$ per block × $\lceil \frac{n}{b} \rceil$ blocks $\rightsquigarrow \Theta(n)$
- ► 3. $\Theta\left(\frac{n}{b}\log(\frac{n}{b})\right) = \Theta(n)$



Compacting subsequences

How do prefix sums help with sorting? one more step to go ...

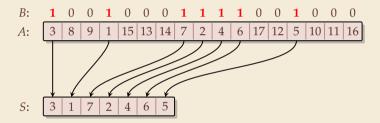
Goal: *Compact* a subsequence of an array



Compacting subsequences

How do prefix sums help with sorting? one more step to go ...

Goal: *Compact* a subsequence of an array



Use prefix sums on bitvector B

 \rightsquigarrow offset of selected cells in *S*

- $_{1} C := B // copy B$
- 2 parallelPrefixSums(C)
- ³ for $j := 0, \ldots, n-1$ do in parallel

4 **if**
$$B[j] == 1$$
 then $S[C[j] - 1] := A[j]$

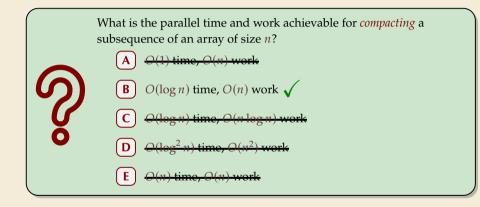
5 end parallel for

Clicker Question

What is the parallel time and work achievable for *compacting* a subsequence of an array of size *n*? O(1) time, O(n) work **B** $O(\log n)$ time, O(n) work **C** $O(\log n)$ time, $O(n \log n)$ work **D** $O(\log^2 n)$ time, $O(n^2)$ work O(n) time, O(n) work



Clicker Question





3.9 Parallel sorting

Parallel quicksort

Let's try to parallelize quicksort

/ about -R (u) time

recursive calls can run in parallel (data independent)

• our sequential partitioning algorithm seems hard to parallelize

Parallel quicksort

Let's try to parallelize quicksort

- recursive calls can run in parallel (data independent)
- our sequential partitioning algorithm seems hard to parallelize
- but can split partitioning into rounds:
 - **1. comparisons:** compare all elements to pivot (in parallel), store result in bitvectors
 - 2. compute prefix sums of bit vectors (in parallel as above)
 - 3. compact subsequences of small and large elements (in parallel as above)

Parallel quicksort – Code

```
procedure parQuicksort(A[l..r))
       b := choosePivot(A[l..r))
2
       i := parallelPartition(A[l..r), b)
3
                                                                                         action 1 11 action 7
       in parallel { parQuicksort(A[1..i]), parQuicksort(A[i+1..r)) }
4
5
6 procedure parallelPartition(A[0..n), b)
       swap(A[n-1], A[b]); p := A[n-1]
7
       for i = 0, \ldots, n - 2 do in parallel
8
           S[i] := [A[i] \le p] // S[i] \text{ is } 1 \text{ or } 0
9
           L[i] := 1 - S[i]
10
      end parallel for
11
       in parallel { parallelPrefixSum(S[0..n-2]); parallelPrefixSum(L[0..n-2]) }
12
13
      i := S[n-2] + 1
       for i = 0, \ldots, n - 2 do in parallel
14
           x := A[i]
15
           if x \le p then A[S[i] - 1] := x
16
           else A[i + L[i]] := x
17
      end parallel for
18
      A[j] := p
19
       return j
20
```

Parallel quicksort – Analysis

► Time:

- ▶ partition: all O(1) time except prefix sums $\rightsquigarrow \Theta(\log n)$ time
- ▶ quicksort: expected depth of recursion tree is $\Theta(\log n)$
- \rightsquigarrow total time $O(\log^2(n))$ in expectation

► Work:

- ▶ partition: O(n) time except prefix sums $\rightsquigarrow \Theta(n \log n)$ work
- \rightsquigarrow quicksort $O(n \log^2(n))$ work in expectation
- using a work-efficient prefix-sums algorithm yields (expected) work-efficient sorting!

Parallel mergesort

► As for quicksort, recursive calls can run in parallel

Parallel mergesort

As for quicksort, recursive calls can run in parallel

▶ how about merging sorted halves *A*[*l*..*m*) and *A*[*m*..*r*)?

Must treat elements independently.

Parallel mergesort

As for quicksort, recursive calls can run in parallel

- ▶ how about merging sorted halves *A*[*l*..*m*) and *A*[*m*..*r*)?
- Must treat elements independently.

,#elements $\leq x$

- correct position of x in sorted output = rank of x breaking ties by position in A
- ▶ # elements $\leq x$ = # elements from A[l..m) that are $\leq x$ + # elements from A[m..r) that are $\leq x$
- ▶ Note: rank in own run is simply the index of *x* in that run
- ▶ find rank in *other* run by binary search -
- $\rightsquigarrow~$ can move it to correct position

Parallel mergesort – Analysis

► Time:

- merge: $\Theta(\log n)$ from binary search, rest O(1)
- mergesort: depth of recursion tree is $\Theta(\log n)$
- \rightsquigarrow total time $O(\log^2(n))$

► Work:

- merge: *n* binary searches $\rightsquigarrow \Theta(n \log n)$
- \rightsquigarrow mergesort: $O(n \log^2(n))$ work

Parallel mergesort – Analysis

Time:

- merge: $\Theta(\log n)$ from binary search, rest O(1)
- mergesort: depth of recursion tree is $\Theta(\log n)$
- \rightsquigarrow total time $O(\log^2(n))$

Work:

• merge: *n* binary searches $\rightsquigarrow \Theta(n \log n)$

 \rightsquigarrow mergesort: $O(n \log^2(n))$ work

• work can be reduced to $\Theta(n)$ for merge

- do full binary searches only for regularly sampled elements
- ranks of remaining elements are sandwiched between sampled ranks
- use a sequential method for small blocks, treat blocks in parallel
- (details omitted)

& exam

Parallel sorting - State of the art

- ▶ more sophisticated methods can sort in *O*(log *n*) parallel time on CREW-PRAM
- practical challenge: small units of work add overhead
- ▶ need a lot of PEs to see improvement from *O*(log *n*) parallel time
- \rightsquigarrow implementations tend to use simpler methods above
 - check the Java library sources for interesting examples! java.util.Arrays.parallelSort(int[])