

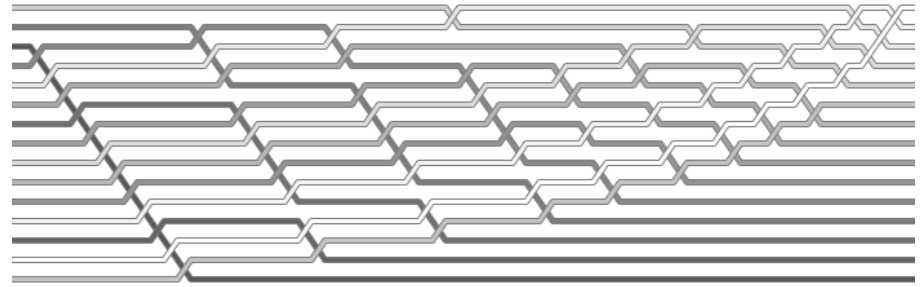
Sorting

Almost half of all CPU cycles are spent on sorting!

- **Input:** array $X[1..n]$ of integers
- **Output:** sorted array (permutation of input)

In: 5,2,9,1,7,3,4,8,6

Out: 1,2,3,4,5,6,7,8,9



- Assume WLOG all input numbers are unique
- Decision tree model \Rightarrow count comparisons “ $<$ ”



Lower Bound for Sorting

Theorem: Sorting requires $\Omega(n \log n)$ time

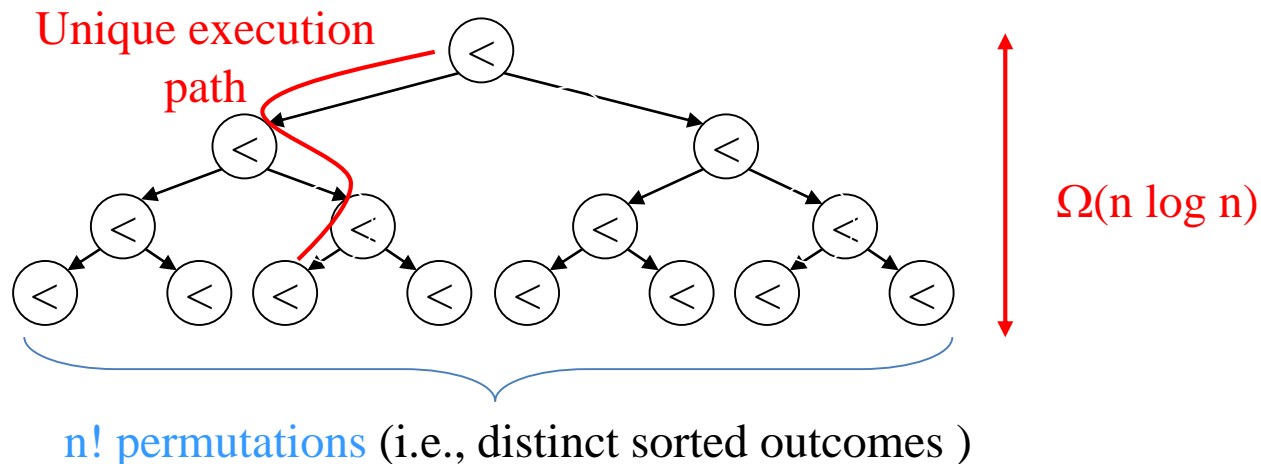
Proof: Assume WLOG unique numbers

\Rightarrow $n!$ different permutations

\Rightarrow comparison decision tree has $n!$ leaves

\Rightarrow tree height $\geq \log(n!) > \log\left(\left(\frac{n}{e}\right)^n\right) = n \cdot \log\left(\frac{n}{e}\right) = \Omega(n \log n)$

$\Rightarrow \Omega(n \log n)$ decisions / time necessary to sort



Sorting Algorithms (Sorted!)

- AKS sort
- Bead sort
- Binary tree sort
- Bitonic sorter
- Block sort
- Bogosort
- Bozo sort
- Bubble sort
- Bucket sort
- Burstersort
- Cocktail sort
- Comb sort
- Counting sort
- Cubesort
- Cycle sort
- Flashsort
- Franceschini's sort
- Gnome sort
- Heapsort
- In-place merge sort
- Insertion sort
- Introspective sort
- Library sort
- Merge sort
- Odd-even sort
- Patience sorting
- Pigeonhole sort
- Postman sort
- Quantum sort
- Quicksort
- Radix Sort
- Sample sort
- Selection sort
- Shaker sort
- Shell sort
- Simple pancake sort
- Sleep sort
- Smoothsort
- Sorting network
- Spaghetti sort
- Splay sort
- Spreadsor
- Stooge sort
- Strand sort
- Timsort
- Tree sort
- Tournament sort
- UnShuffle Sort

Sorting Algorithms

Q: Why so many sorting algorithms?

A: There is no “**best**” sorting algorithm!

Some considerations:

- **Worst** case?
- **Average** case?
- In practice?
- Input **distribution**?
- Near-sorted data?
- **Stability**?
- **In-situ**?
- Randomized?
- Stack depth?
- Internal vs. **external**?
- Pipeline compatible?
- **Parallelizable**?
- Locality?
- **Online**



Problem: Given n pairs of integers (x_i, y_i) , where $0 \leq x_i \leq n$ and $1 \leq y_i \leq n$ for $1 \leq i \leq n$, find an algorithm that sorts all n ratios x_i / y_i in linear time $O(n)$.

- What approaches fail?
- What techniques work and why?
- Lessons and generalizations

Problem: Given n integers, find in $O(n)$ time the majority element (i.e., occurring $\geq n/2$ times, if any).

- What approaches fail?
- What techniques work and why?
- Lessons and generalizations

Problem: Given n objects, find in $O(n)$ time the **majority** element (i.e., occurring $\geq n/2$ times, if any), using only equality comparisons ($=$).

- What approaches fail?
- What techniques work and why?
- Lessons and generalizations

Problem: Given n integers, find both the **maximum** and the **next-to-maximum** using the least number of comparisons (**exact** comparison count, not just $O(n)$).

- What approaches fail?
- What techniques work and why?
- Lessons and generalizations

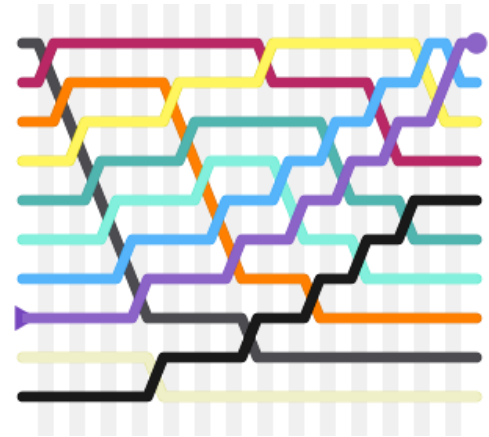
Bubble Sort

Input: array $X[1..n]$ of integers

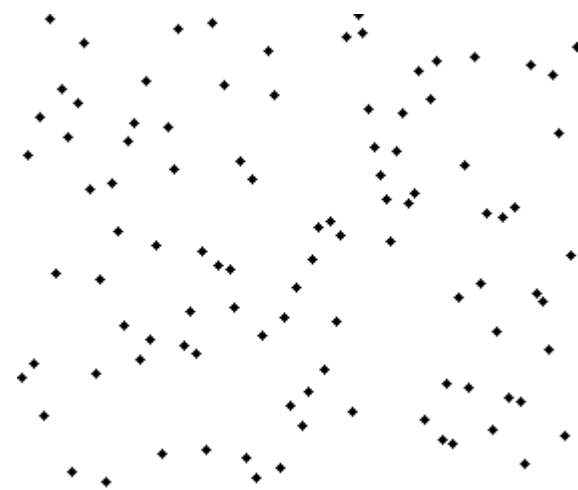
Output: sorted array (monotonic permutation)

Idea: keep swapping adjacent pairs

```
until array X is sorted do
  for i=1 to n-1
    if  $X[i+1] < X[i]$ 
      then swap(X,i,i+1)
```



6 5 3 1 8 7 2 4



- $O(n^2)$ time **worst**-case, but sometimes faster
- **Adaptive**, **stable**, in-situ, **slow**

Odd-Even Sort



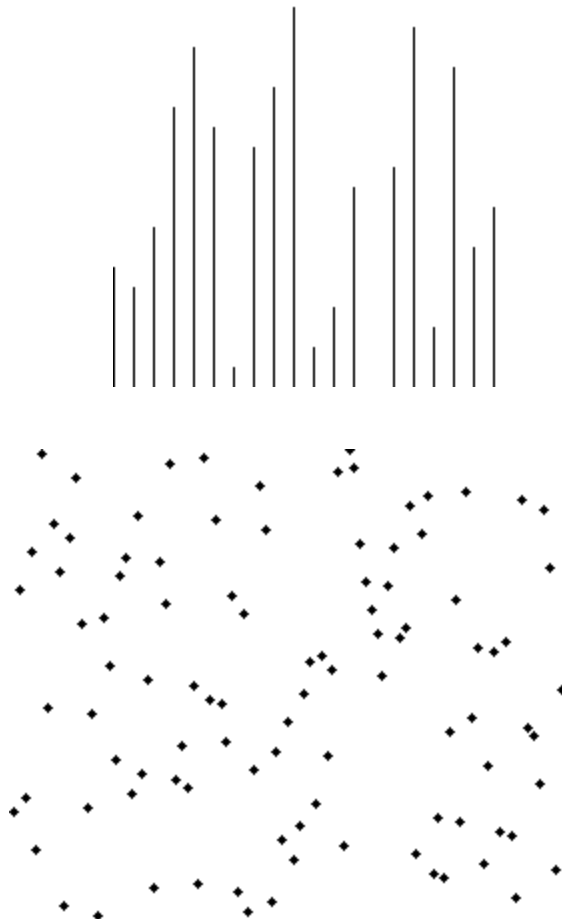
Input: array $X[1..n]$ of integers

Output: sorted array (monotonic)

Idea: swap even and odd pairs

```
until array  $X$  is sorted do
  for even  $i=1$  to  $n-1$ 
    if  $X[i+1] < X[i]$  swap( $X, i, i+1$ )
  for odd  $i=1$  to  $n-1$ 
    if  $X[i+1] < X[i]$  swap( $X, i, i+1$ )
```

- $O(n^2)$ time worst-case,
but faster on near-sorted data
- **Adaptive**, **stable**, in-situ, **parallel**



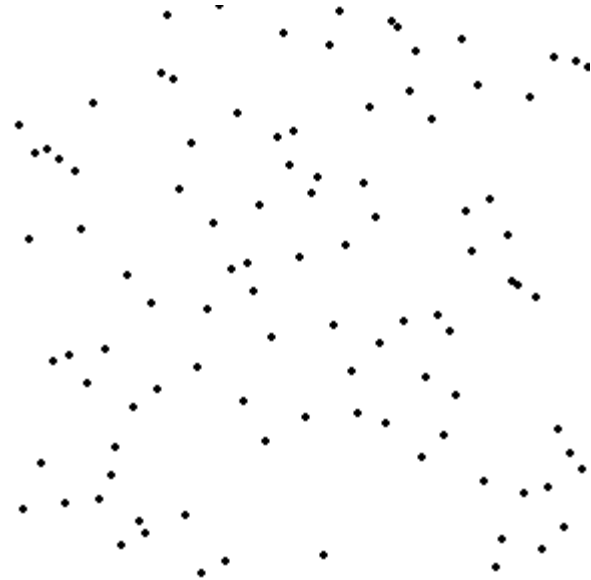
Selection Sort

Input: array $X[1..n]$ of integers

Output: sorted array (monotonic permutation)

Idea: move the largest to current pos

```
for i=1 to n-1
  let X[j] be largest
  among X[i..n]
  swap(X,i,j)
```



8
5
2
6
9
3
1
4
0
7

- $\Theta(n^2)$ time worst-case
- **Stable**, **in-situ**, simple, **not** adaptive
- Relatively fast (among quadratic sorts)

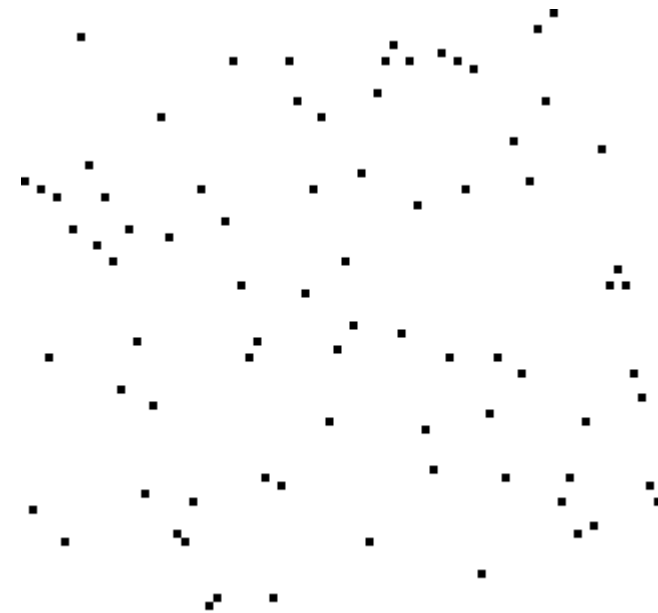
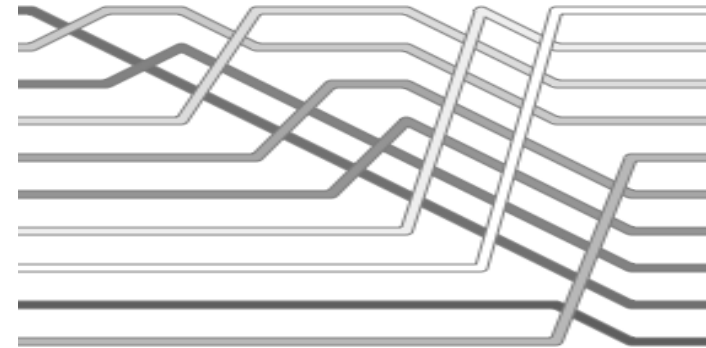
Insertion Sort

6 5 3 1 8 7 2 4

- **Input**: array $X[1..n]$ of integers
- **Output**: sorted array (monotonic permutation)

Idea: insert each item into list

```
for i=2 to n
  insert X[i] into the
  sorted list X[1..(i-1)]
```



- $O(n^2)$ time worst-case
- $O(nk)$ where k is max dist of any item from final sorted pos
- **Adaptive**, **stable**, **in-situ**, online

Heap Sort

Input: array $X[1..n]$ of integers

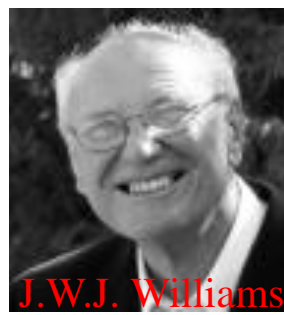
Output: sorted array (monotonic)

Idea: exploit a heap to sort

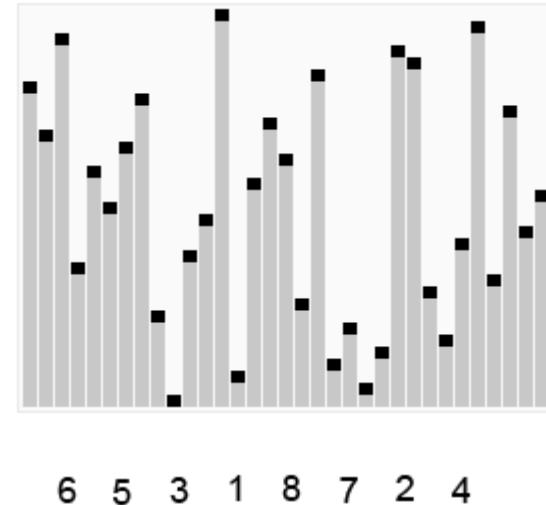
```
InitializeHeap
For i=1 to n HeapInsert(X[i])
For i=1 to n do
    M=HeapMax; Print(M)
    HeapDelete(M)
```



Robert Floyd

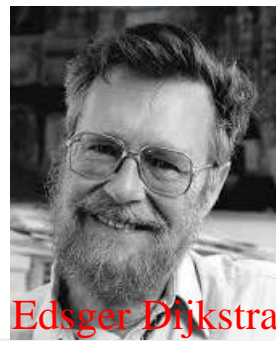


J.W.J. Williams



- $\Theta(n \log n)$ optimal time
- **Not** stable, **not** adaptive, in-situ

SmoothSort



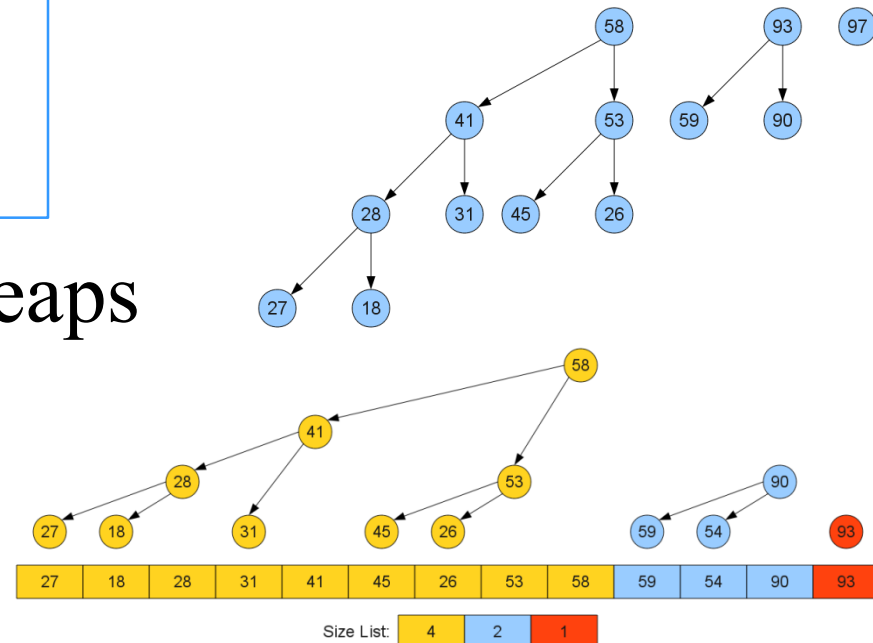
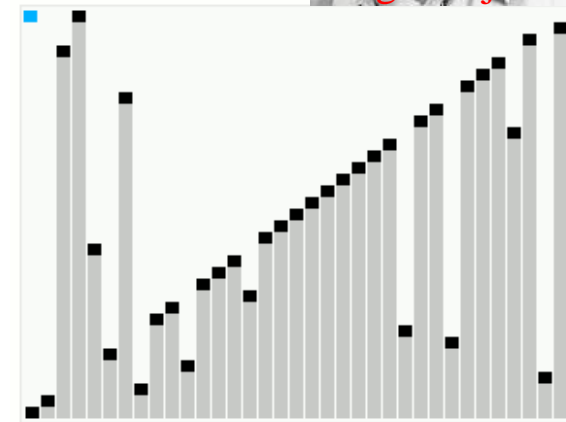
Input: array $X[1..n]$ of integers

Output: sorted array (monotone)

Idea: adaptive heapsort

```
InitializeHeaps
for i=1 to n HeapsInsert(X[i])
for i=1 to n do
  M=HeapsMax; Print(M)
  HeapsDelete(M)
```

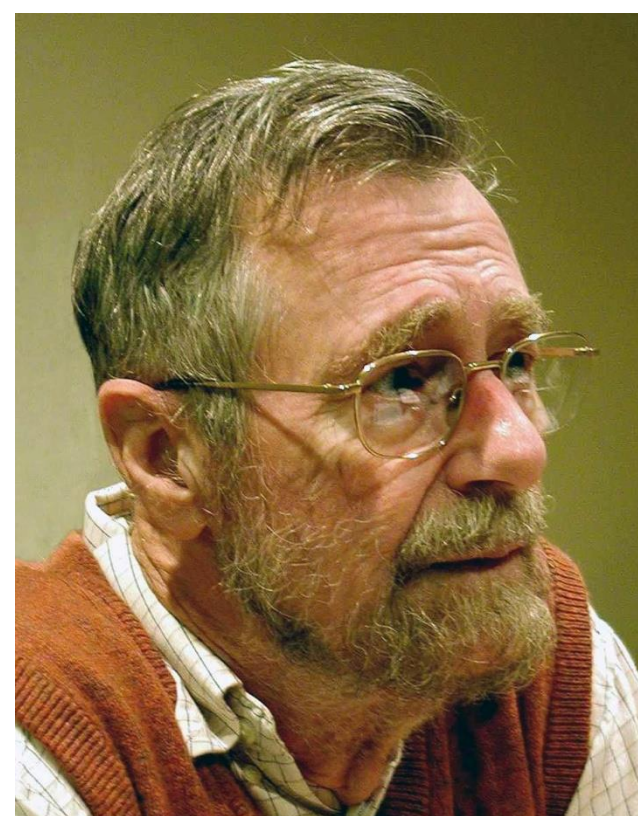
- Uses multiple (Leonardo) heaps
- $O(n \log n)$
- $O(n)$ if list is mostly sorted
- **Not** stable, **adaptive**, in-situ



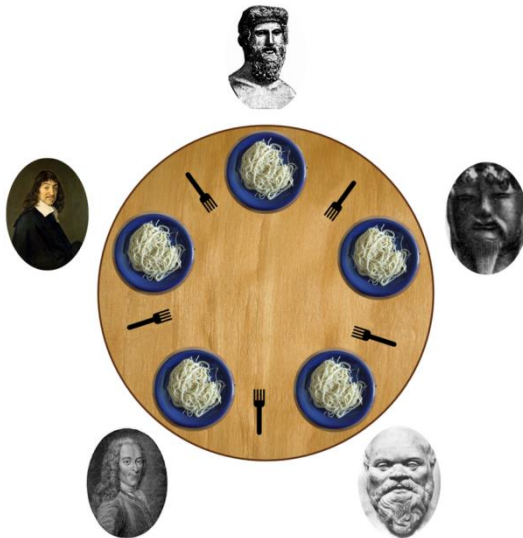
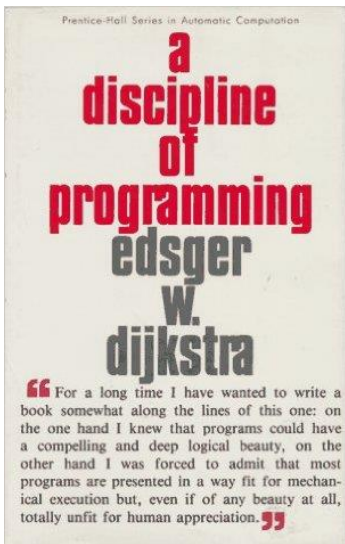
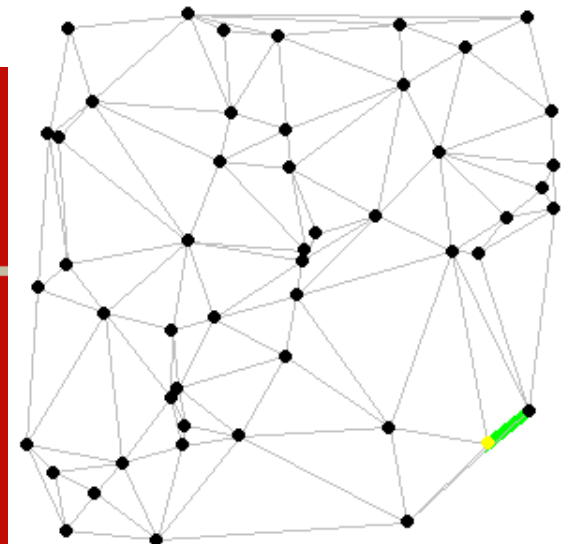
Historical Perspectives

Edsger W. Dijkstra (1930-2002)

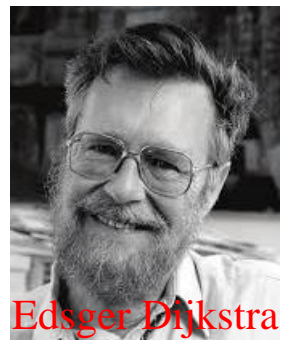
- Pioneered **software engineering**, OS design
- Invented **concurrent programming**, **mutual exclusion** / semaphores
- Invented **shortest paths** algorithm
- Advocated **structured** (GOTO-less) code
- Stressed **elegance** & **simplicity** in design
- Won Turing Award in 1972



Dijkstra's algorithm



Quotes by Edsger W. Dijkstra (1930-2002)



- “**Computer science** is no more about computers than astronomy is about telescopes.”
- “If **debugging** is the process of removing software bugs, then **programming** must be the process of putting them in.”
- “**Testing** shows the presence, not the absence of bugs.”
- “**Simplicity** is prerequisite for reliability.”
- “The use of **COBOL** cripples the mind; its teaching should, therefore, be regarded as a criminal offense.”
- “**Object-oriented programming** is an exceptionally bad idea which could only have originated in California.”
- “**Elegance** has the disadvantage, if that's what it is, that hard work is needed to achieve it and a good education to appreciate it.”

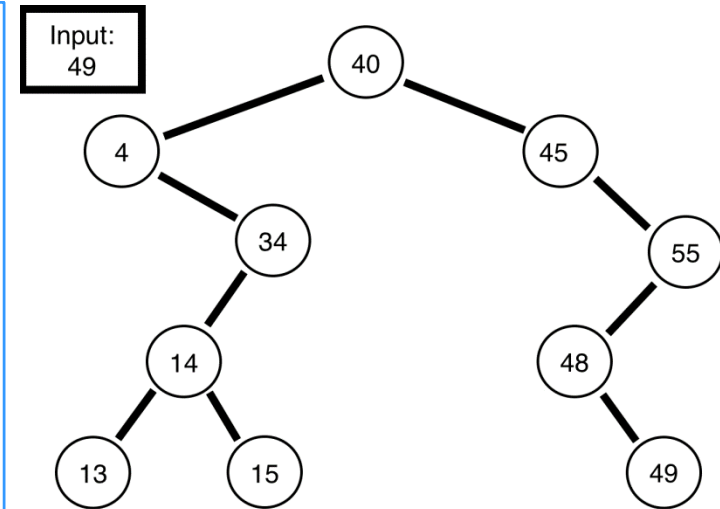


Generalizing Heap Sort

Input: array $X[1..n]$ of integers

Output: sorted array

```
InitializeTree
For i=1 to n
    TreeInsert(X[i])
For i=1 to n do
    M=TreeMax; Print(M)
    TreeDelete(M)
```



- **Observation:** other data structures can work here!
- Ex: replace heap with any **height-balanced tree**
- Retains $O(n \log n)$ worst-case time!

Tree Sort

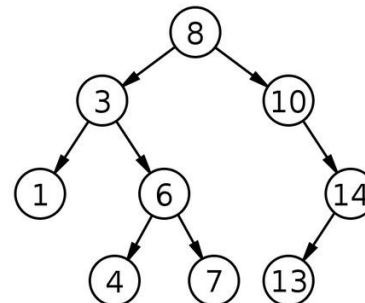
Input: array $X[1..n]$ of integers

Output: sorted array (monotonic)

Idea: populate a tree & traverse

```
InitializeTree
for i=1 to n TreeInsert(X[i])
traverse tree in-order
to produce sorted list
```

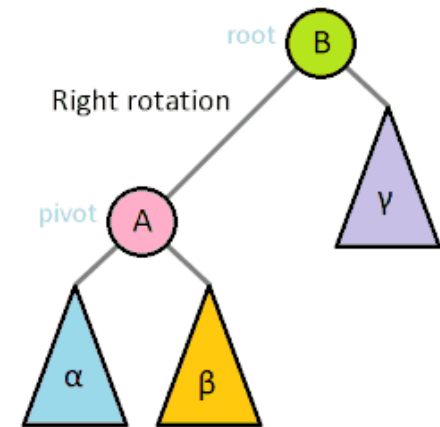
- Use balanced tree (AVL, B, 2-3, splay)
- $O(n \log n)$ time worst-case
- Faster for near-sorted inputs
- **Stable, adaptive**, simple



B-Tree Sort

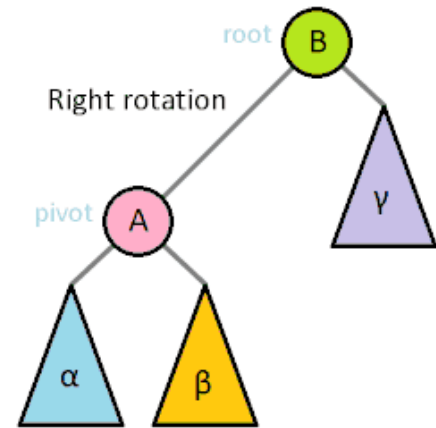


- Multi-rotations occur infrequently
- Rotations don't propagate far
- Larger tree \Rightarrow fewer rotations
- Same for other height-balanced trees
- Non-balanced search trees **average $O(\log n)$ height**



AVL-Tree Sort

- Multi-rotations occur infrequently
- Rotations don't propagate far
- Larger tree \Rightarrow fewer rotations
- Same for other height-balanced trees
- Non-balanced trees **average $O(\log n)$ height**



Merge Sort



Input: array $X[1..n]$ of integers

Output: sorted array (monotonic)

Idea: sort sublists & merge them

MergeSort(X, i, j)

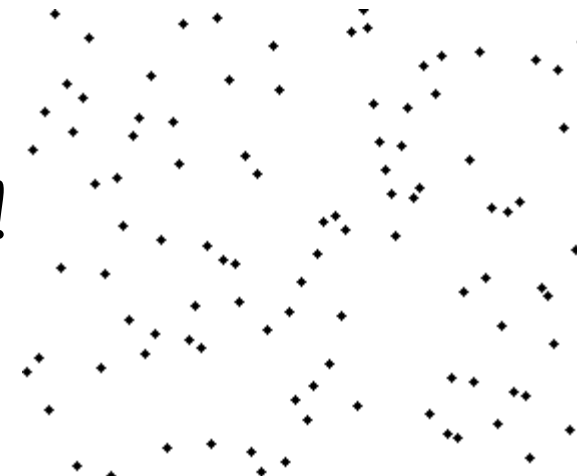
if $i < j$ then $m = \lfloor (i+j)/2 \rfloor$

MergeSort($X, i..m$)

MergeSort($X, m+1..j$)

Merge($X, i..m, m+1..j$)

6 5 3 1 8 7 2 4



- $T(n) = 2T(n/2) + n = \Theta(n \log n)$ **optimal!**
- **Stable**, **parallelizes**, **not** in-situ
- Can be made **in-situ** & stable

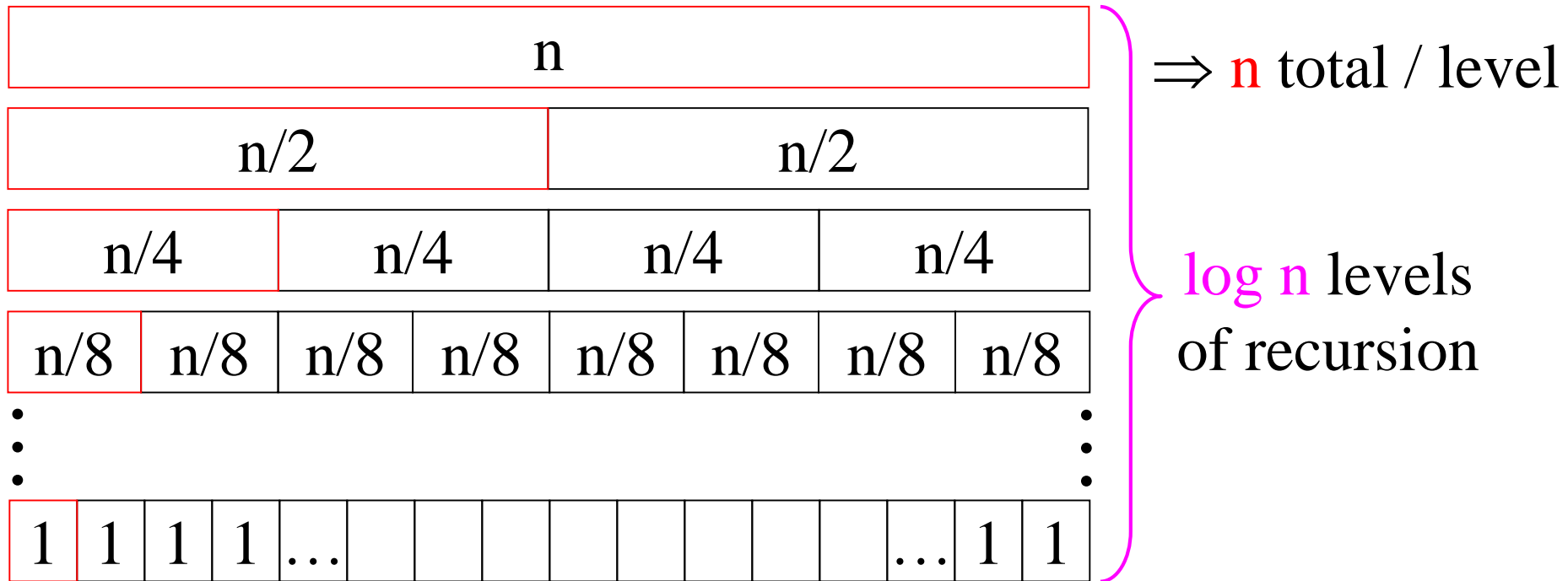
Merge Sort



Theorem: MergeSort runs within time $\Theta(n \log n)$ which is **optimal**.

Proof: Even-split divide & conquer:

$$T(n) = 2 \cdot T(n/2) + n$$



Total time is $O(n \log n)$; $\Omega(n \log n) \Rightarrow \Theta(n \log n)$

Quicksort



Input: array $X[1..n]$ of integers

Output: sorted array (monotonic)

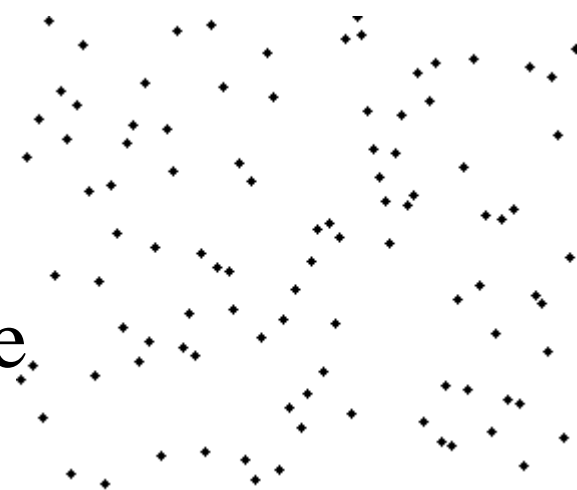
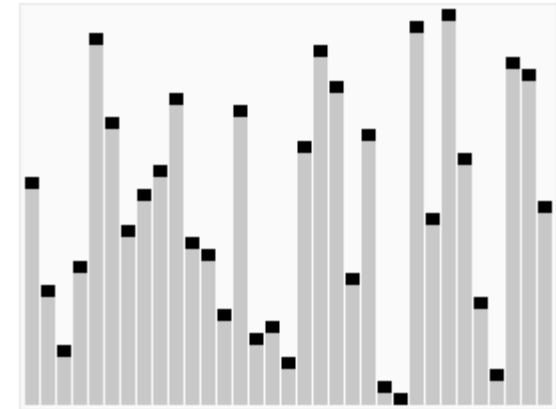
Idea: sort two sublists around pivot

QuickSort(X, i, j)

If $i < j$ Then $p = \text{Partition}(X, i, j)$

QuickSort(X, i, p)

QuickSort($X, p+1, j$)



- $\Theta(n \log n)$ time average-case
- $\Theta(n^2)$ worst-case time (rare)
- **Unstable**, **parallelizes**, $O(\log n)$ space
- Ave: only beats $\Theta(n^2)$ sorts for $n > 40$

Shell Sort



Donald Shell

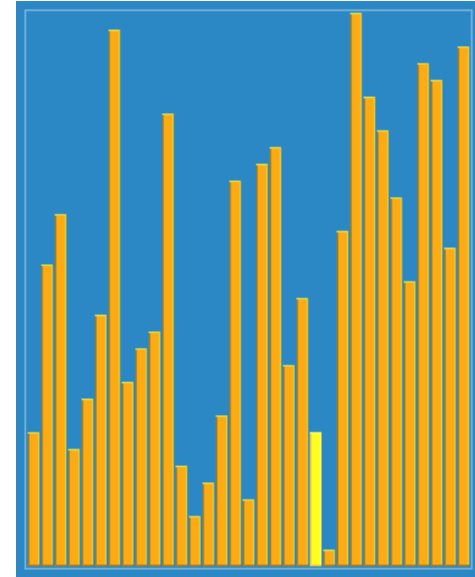
Input: array $X[1..n]$ of integers

Output: sorted array (monotonic)

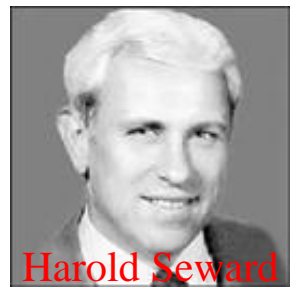
Idea: generalize insertion sort

for each h_i in sequence $h_k, \dots, h_1=1$
Insertion-sort all items h_i apart

- Array is sorted after last pass ($h_i=1$)
- Long swaps quickly reduce disorder
- $O(n^2)$, $O(n^{3/2})$, $O(n^{4/3})$, ... ?
- Complexity still **open problem!**
- LB is $\Omega(N(\log/\log \log n)^2)$
- **Not** stable, **adaptive**, **in-situ**



Counting Sort



Harold Seward

Q: Why not use counting sort for arbitrary 32-bit integers? (i.e., range k is “fixed”)

A: Range is fixed (2^{32}) but very large (4,294,967,296).
Space/time: the counts array will be huge (4 GB)

Much worse for 64-bit integers ($2^{64} > 10^{19}$):

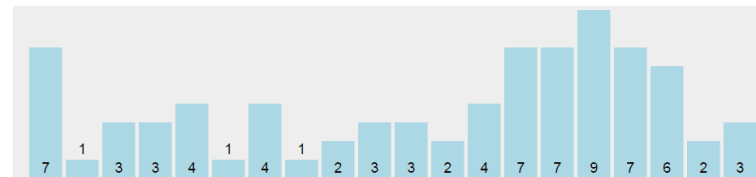
Time: 5 GHz PC will take over $2^{64} / (5 \cdot 10^9) / (60 \cdot 60 \cdot 24 \cdot 365)$ sec **> 116 years** to initialize array!

Memory: $2^{64} > 10^{19} > 18$ Exabytes

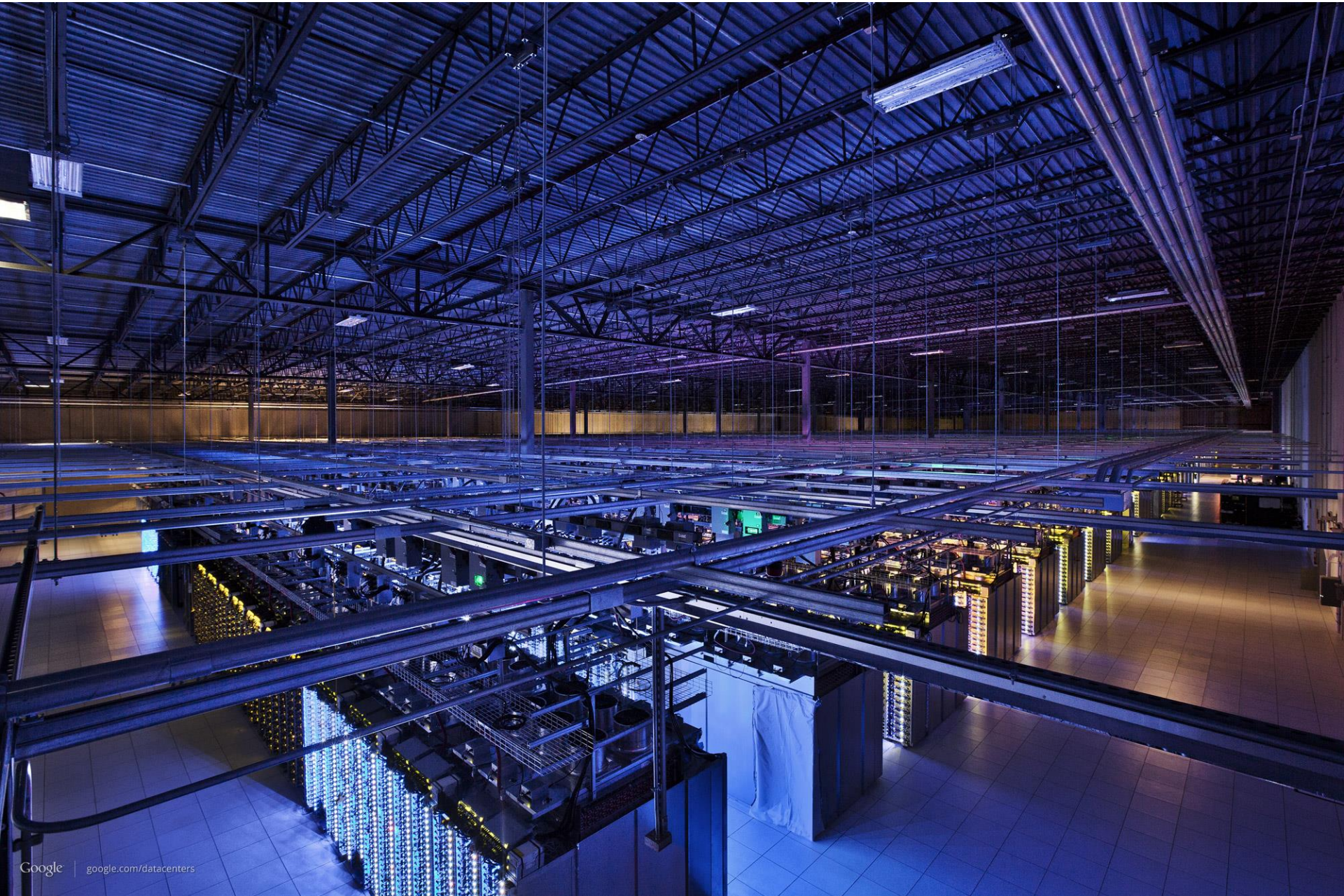
> 2.3 million TB RAM chips!

> total amount of Google's data!

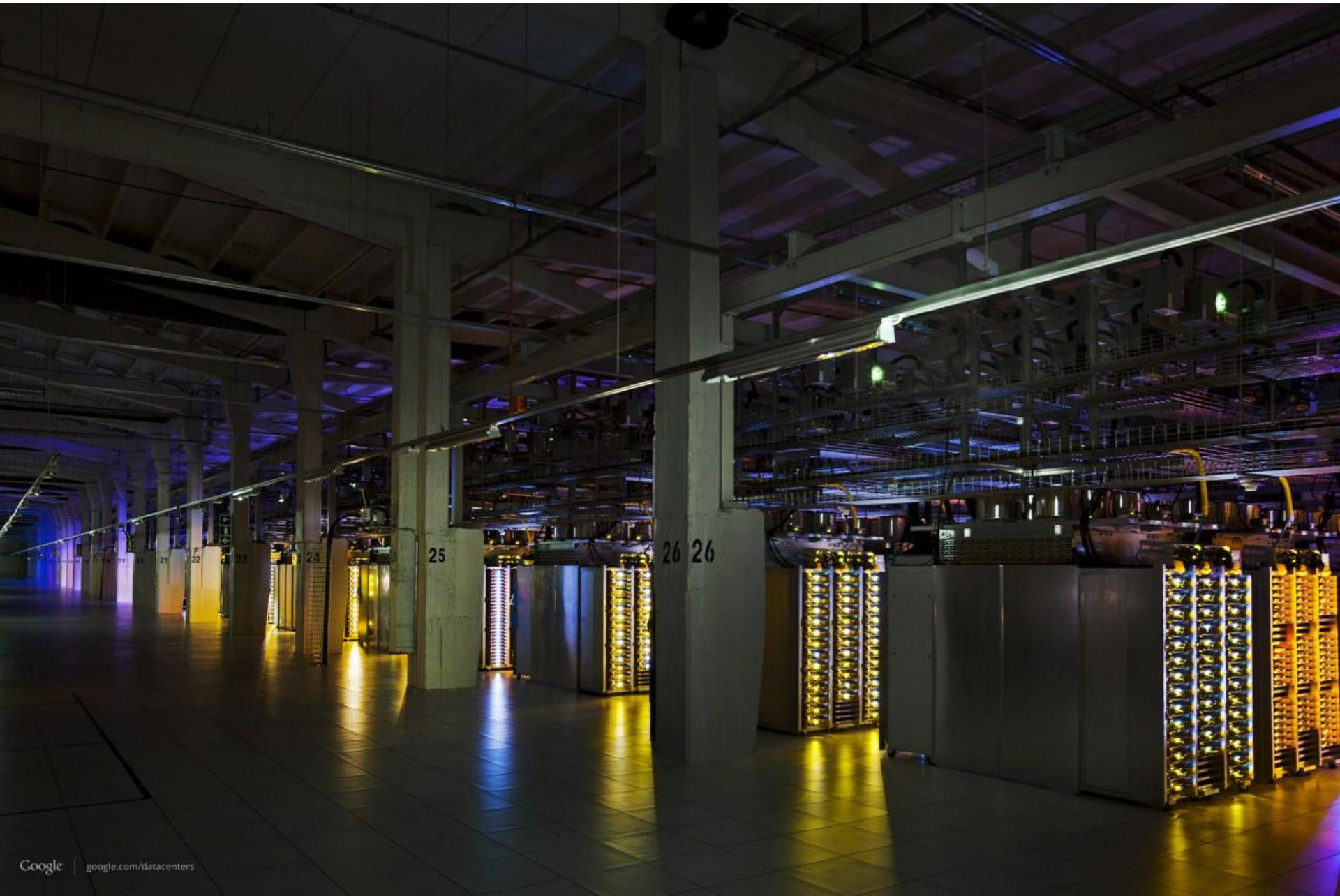
Q: What's an Exabyte? (10^{18})



What does an Exabyte look like?



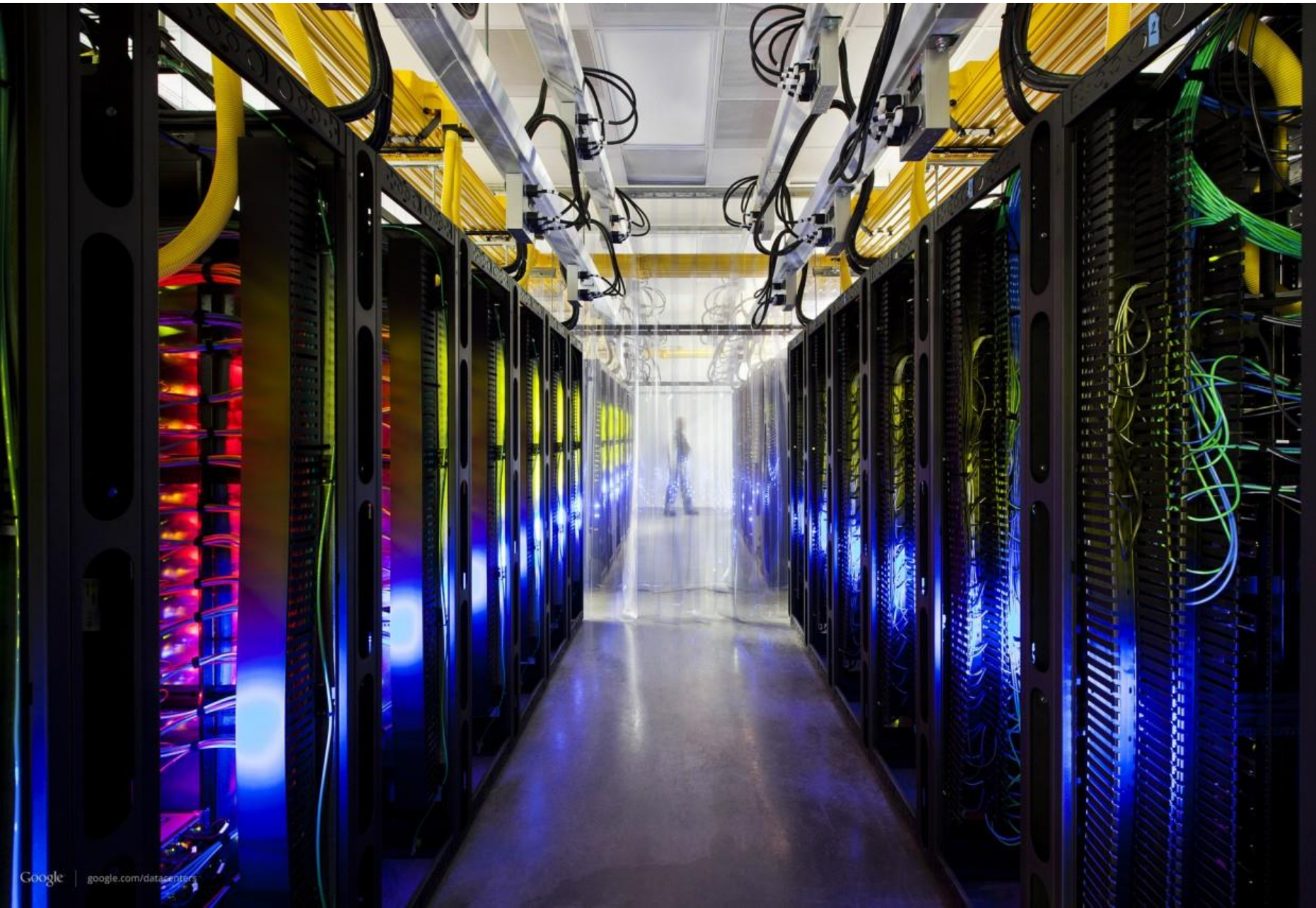
What does an Exabyte look like?



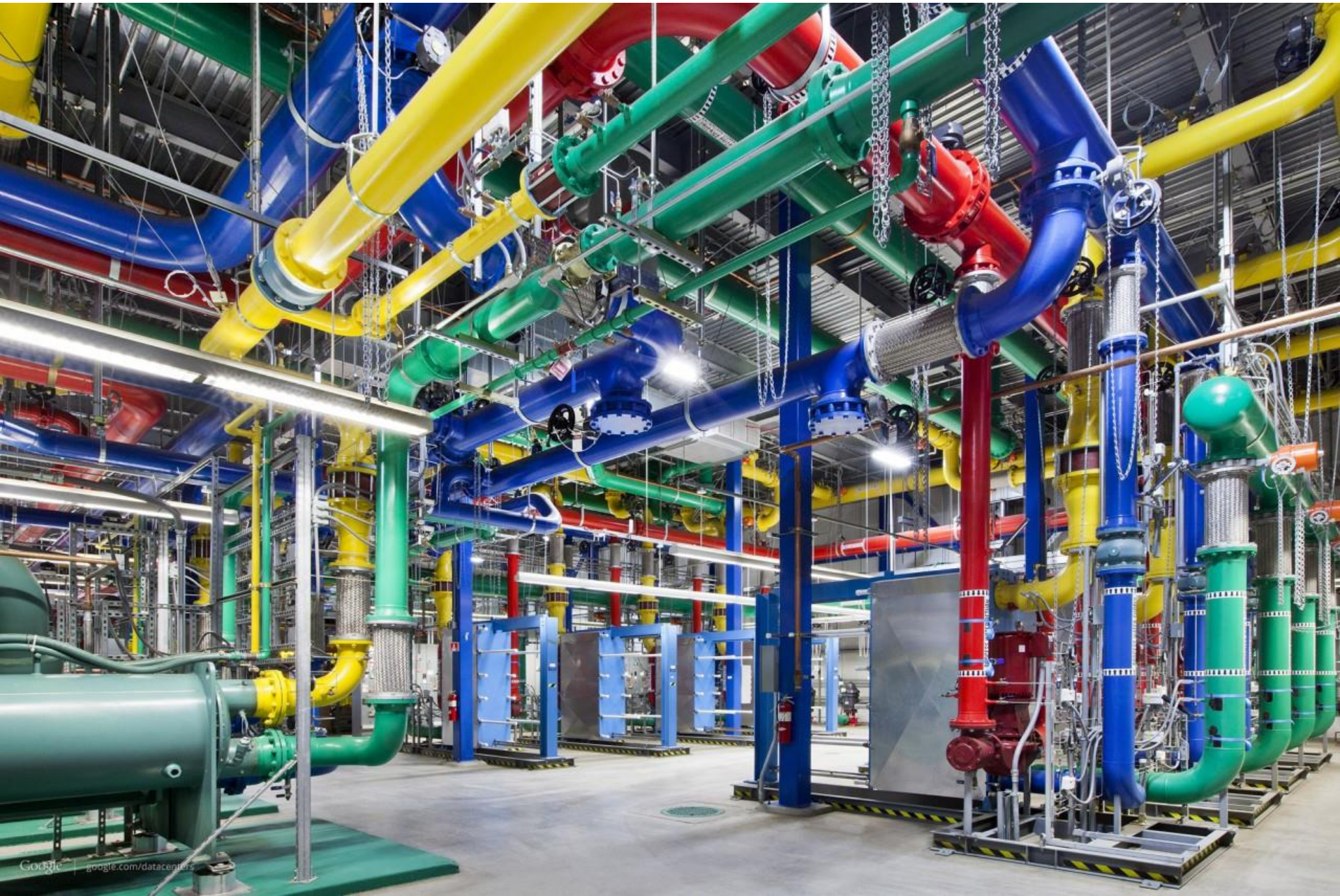
What does an Exabyte look like?



What does an Exabyte look like?



What does an Exabyte look like?

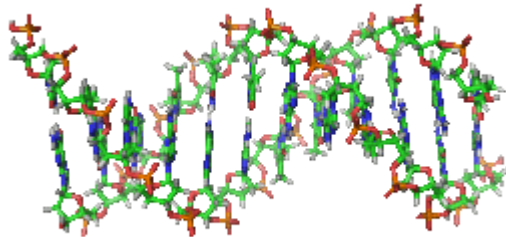


What does an Exabyte look like?



What does an Exabyte look like?

- All content of **Library of Congress**: ~ 0.001 Exabytes
- Total words **ever spoken** by humans: ~ 5 Exabytes
- Total data stored by **Google**: ~ 15 Exabytes
- Total monthly world **internet traffic**: ~ 110 Exabytes
- Storage capacity of **1 gram of DNA**: ~ 455 Exabytes



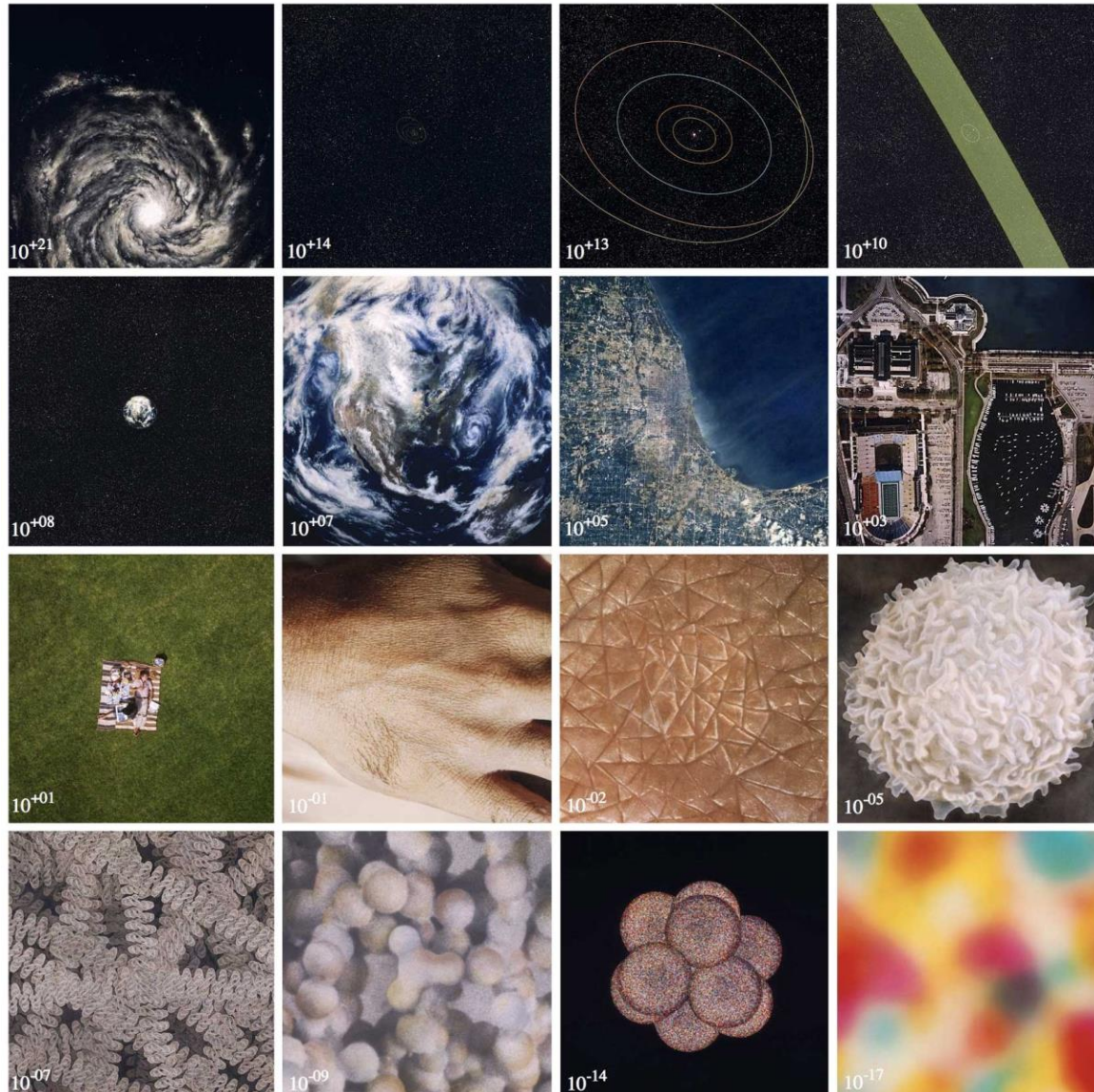
Orders-of-Magnitude

Standard International (SI) quantities:

Deca	10^1	Deci	10^{-1}
Hecto	10^2	Centi	10^{-2}
Kilo	10^3	Milli	10^{-3}
Mega	10^6	Micro	10^{-6}
Giga	10^9	Nano	10^{-9}
Tera	10^{12}	Pico	10^{-12}
Peta	10^{15}	Femto	10^{-15}
Exa	10^{18}	Atto	10^{-18}
Zetta	10^{21}	Zepto	10^{-21}
Yotta	10^{24}	Yocto	10^{-24}

Orders-of-Magnitude

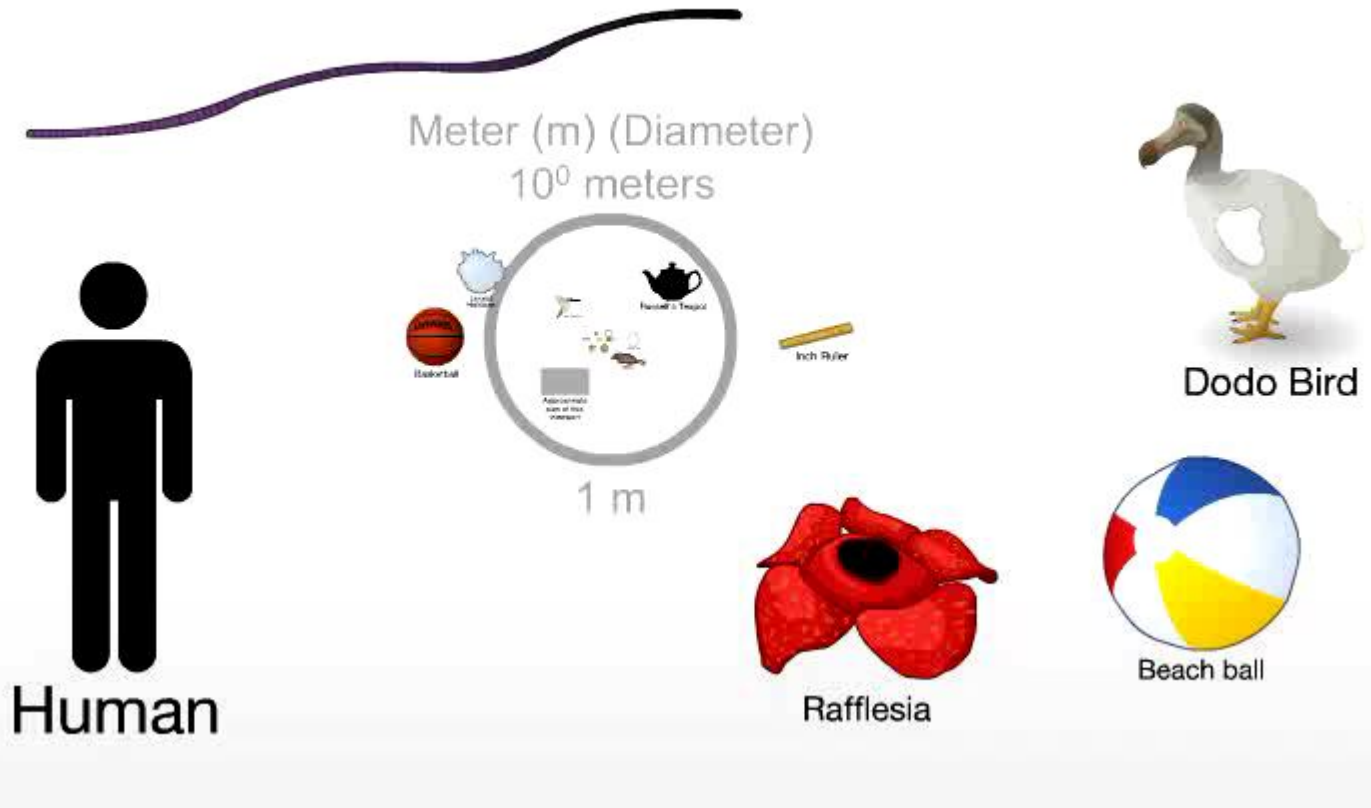
- [“Powers of Ten”](#), Charles and Ray Eames, 1977



Orders-of-Magnitude

- “[Scale of the Universe](#)”, Cary and Michael Huang, 2012

Giant Earthworm



- 10^{-24} to 10^{26} meters \Rightarrow 50 orders of magnitude!

Bucket Sort

Input: array $X[1..n]$ of real numbers in $[0,1]$

Output: sorted array (monotonic)

Idea: spread data among buckets

```
for i=1 to n do
  insert  $X[i]$  into bucket  $\lfloor n \cdot X[i] \rfloor$ 
for i=1 to n do Sort bucket i
concatenate all the buckets
```

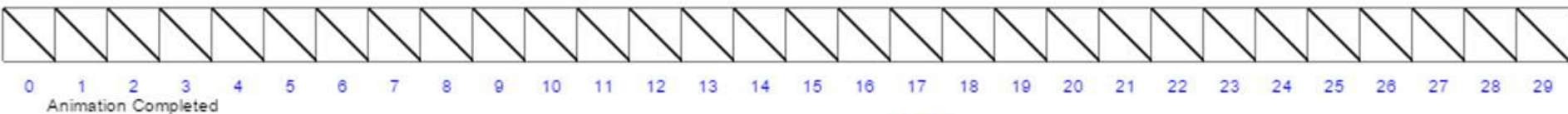
- $O(n+k)$ time **expected**, $O(n)$ space
- $O(\mathbf{Sort})$ time worst-case
- **Assumes** substantial data uniformity
- **Stable**, **parallel**, **not** in-situ
- Generalizes counting sort / quicksort



Bucket Sort

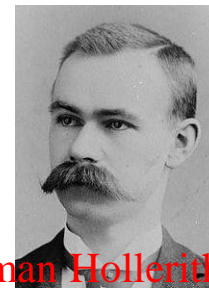


948	847	123	837	176	588	467	689	763	337	347	130	529	878	868	92	882	305	906	749	871	5	552	596	86	216	561	994	388	219
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29

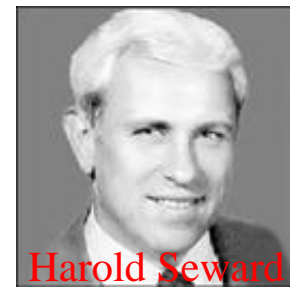


Q: How does bucket sort generalize counting sort? Quicksort?

Radix Sort



Herman Hollerith



Harold Seward

Input: array $X[1..n]$ of integers
each with d digits in **range** $1..k$

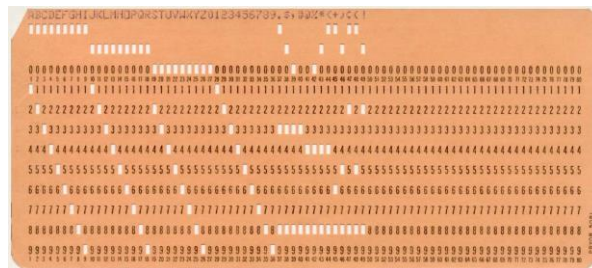
Output: sorted array (monotonic)

Idea: sort each digit in turn

For $i=1$ to d do
 StableSort(X on digit i)



- Makes d calls to **bucket** sort
- $\Theta(d \cdot n)$ time, $\Theta(k+n)$ space
- Not comparison-based
- **Stable**
- **Parallel**
- **Not in-situ**



Radix Sort

6428

4754

9650

5650

9843

7118

8804

3871

6592

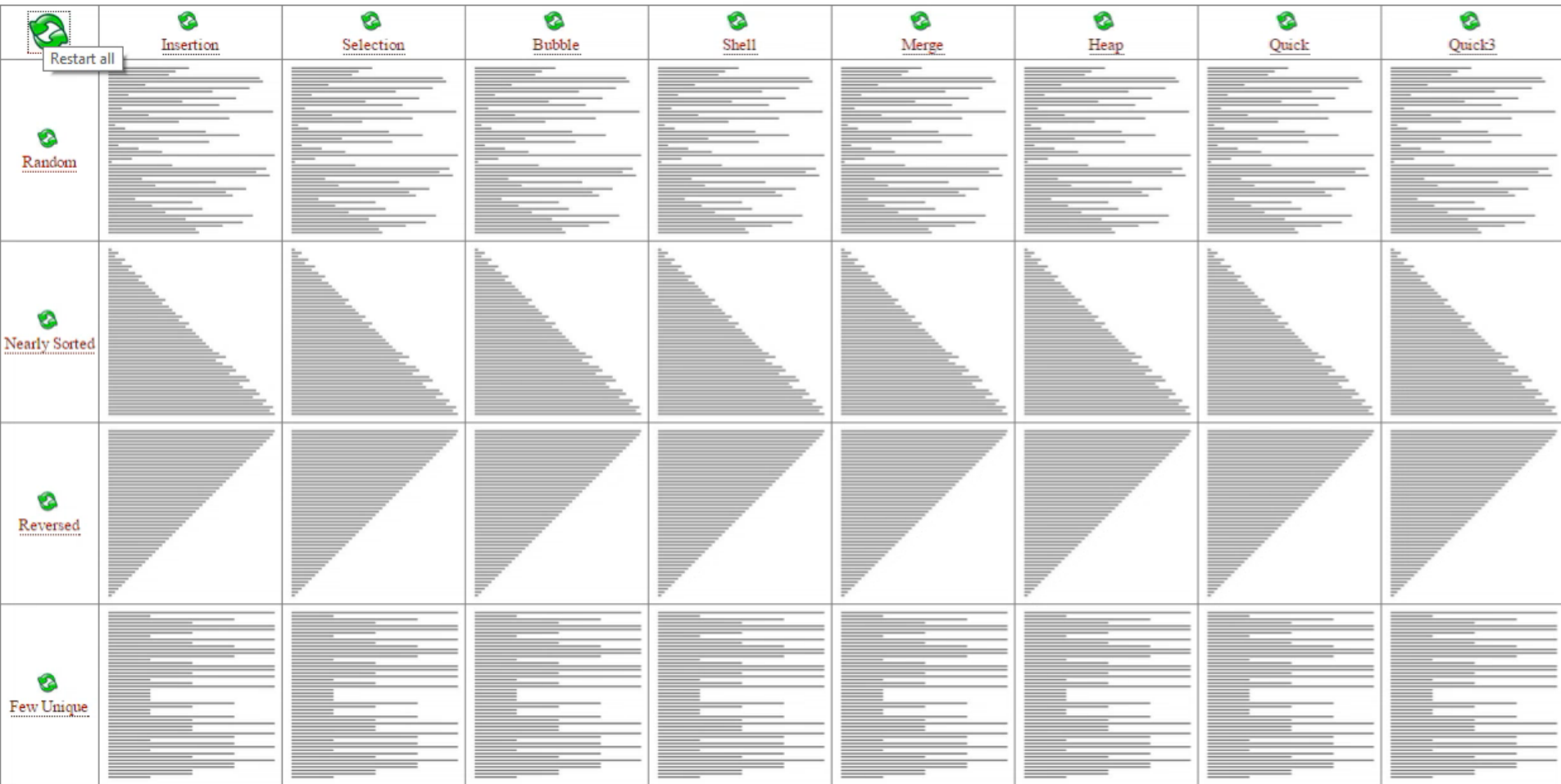
1163

2899

9602

Q: is Radix Sort faster than Merge Sort? $\Theta(d \cdot n)$ vs. $\Theta(n \log n)$

Sorting Comparison



- $O(n \log n)$ sorts tend to beat the $O(n^2)$ sorts ($n > 50$)
- Some sorts work faster on **random** data vs. near-sorted data
- For more details see <http://www.sorting-algorithms.com>

Meta Sort

Q: how can we easily modify quicksort to have $O(n \log n)$ worst-case time?

Idea: **combine** two algorithms to **leverage** the **best** behaviors of **each** one.

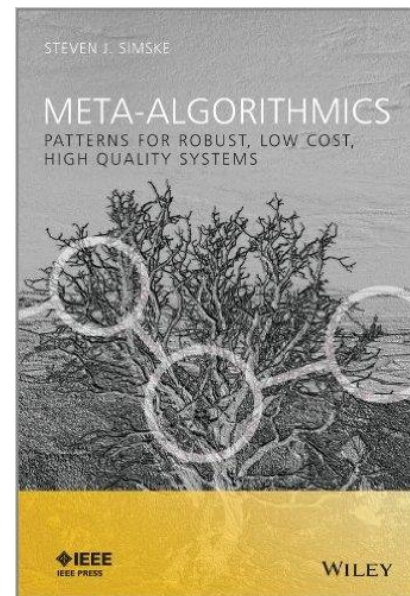
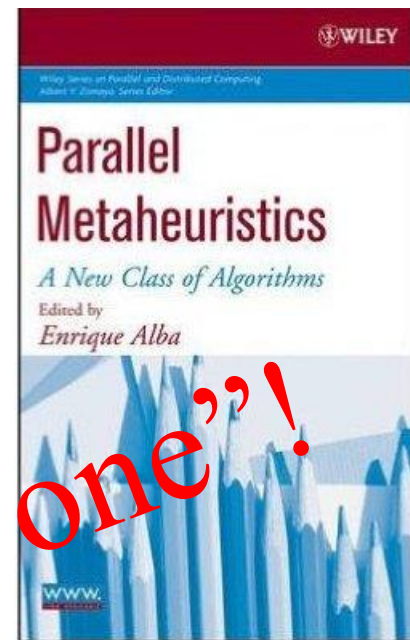
MetaSort(X, i, j):

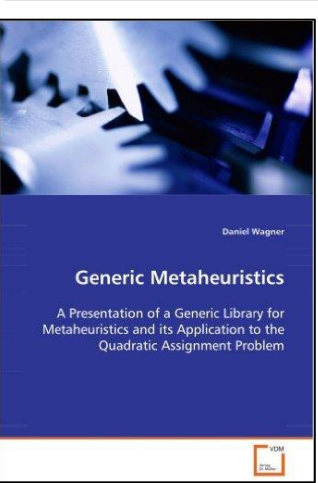
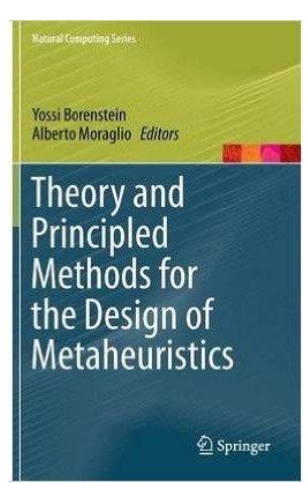
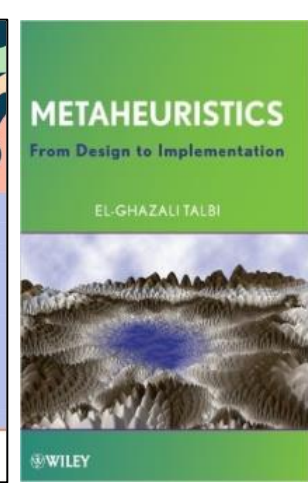
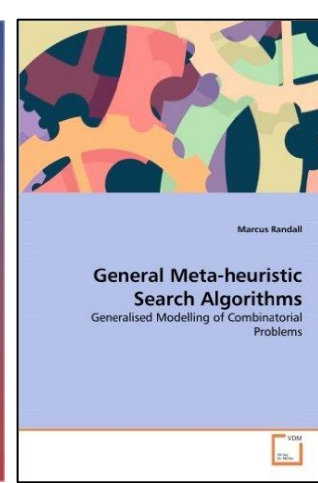
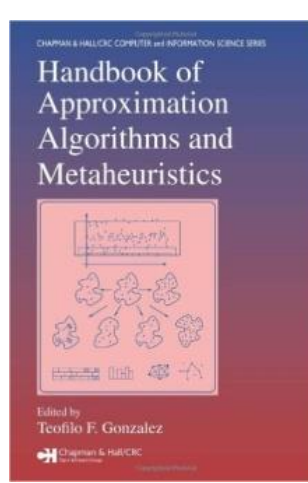
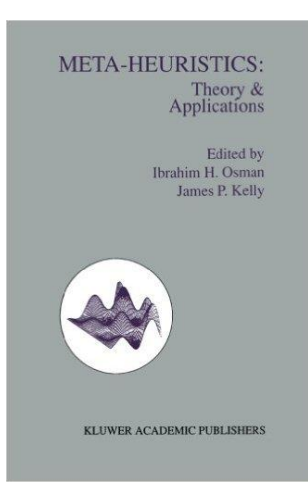
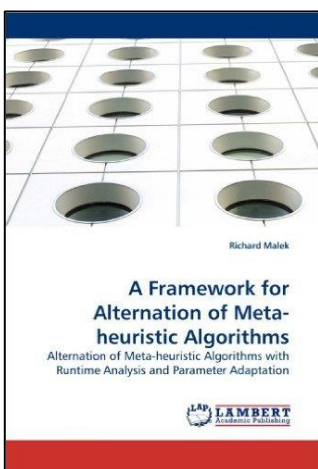
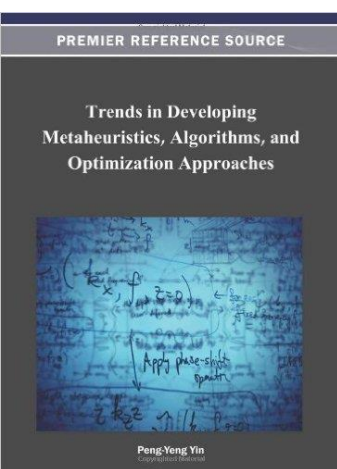
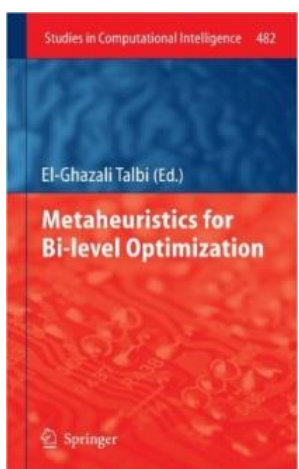
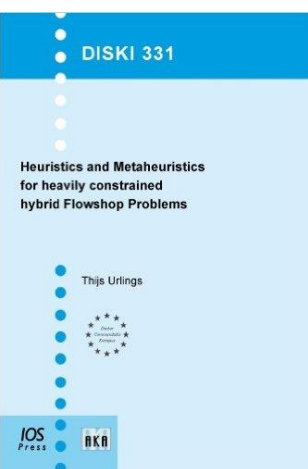
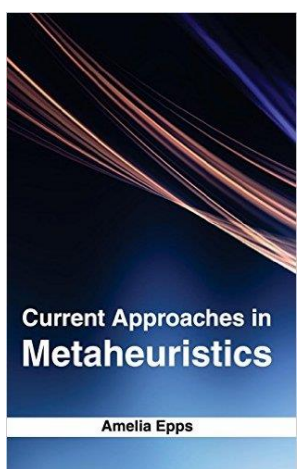
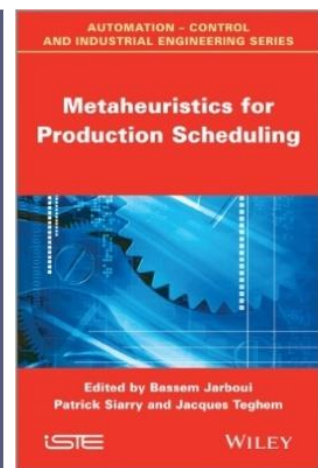
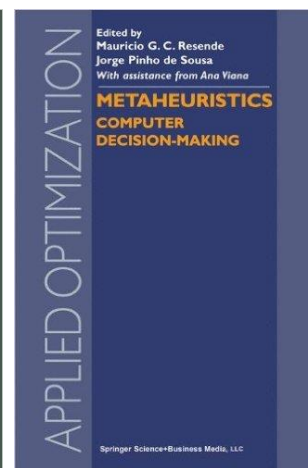
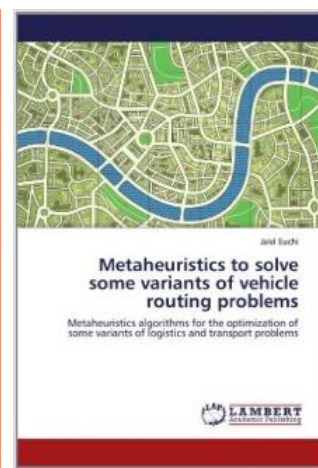
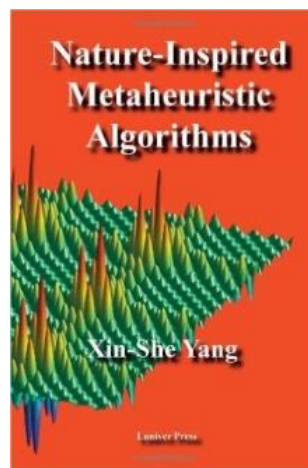
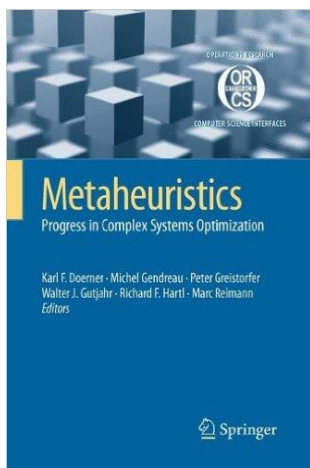
parallel-run:

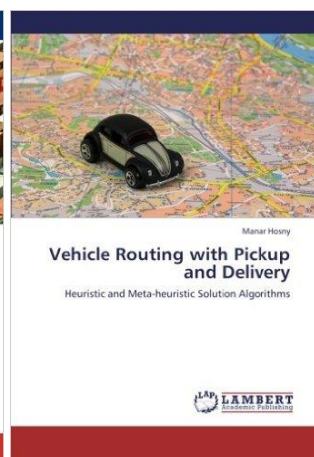
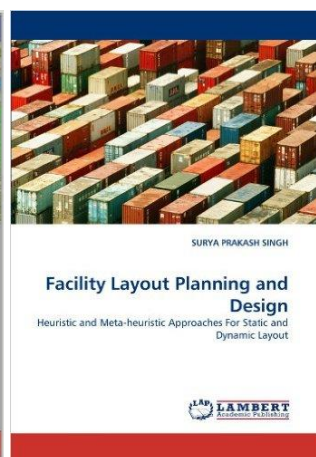
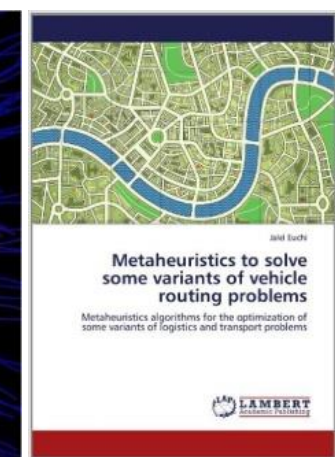
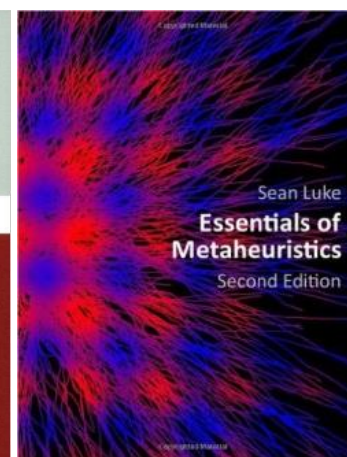
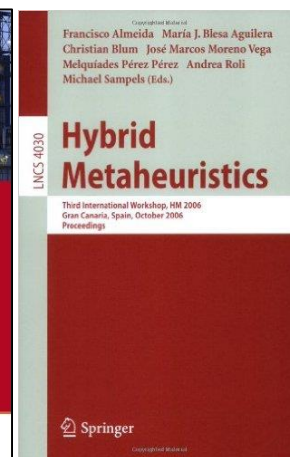
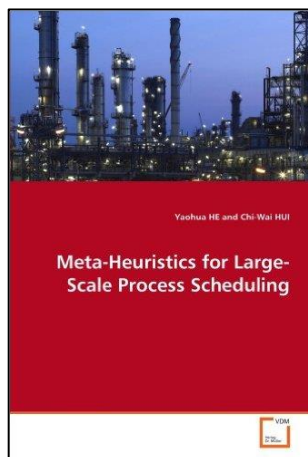
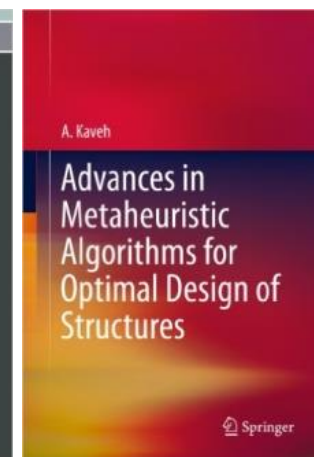
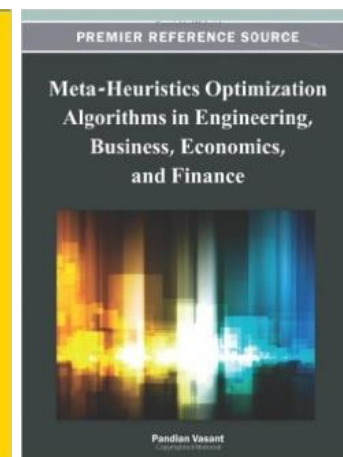
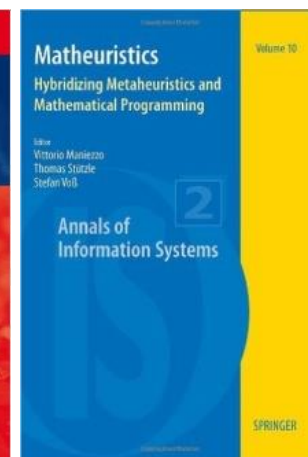
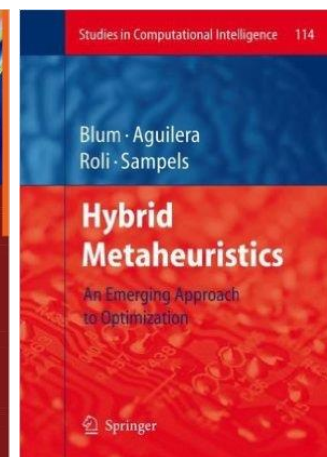
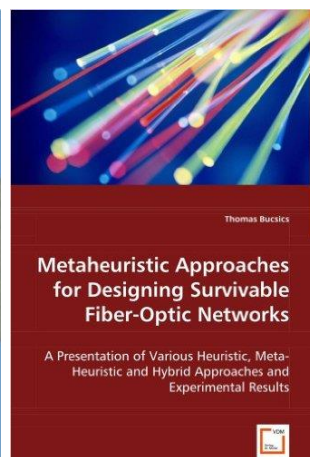
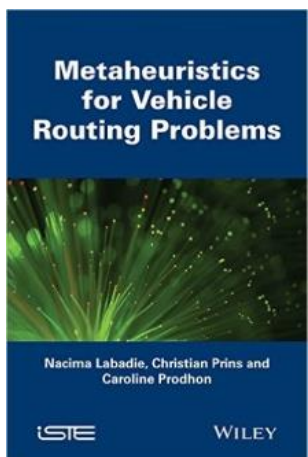
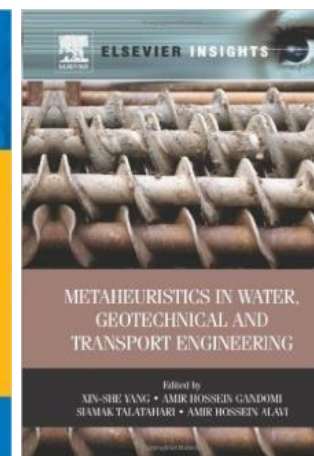
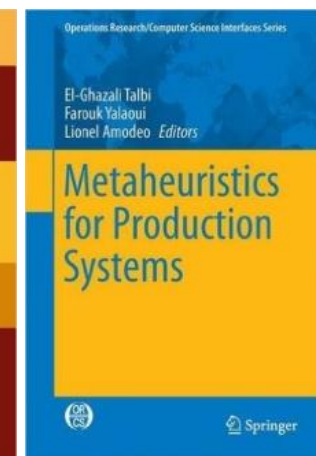
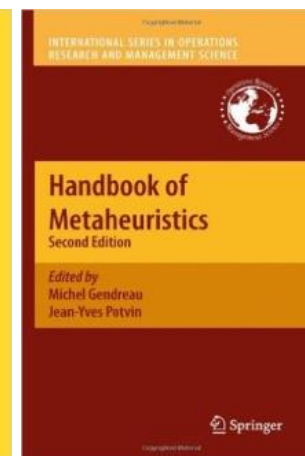
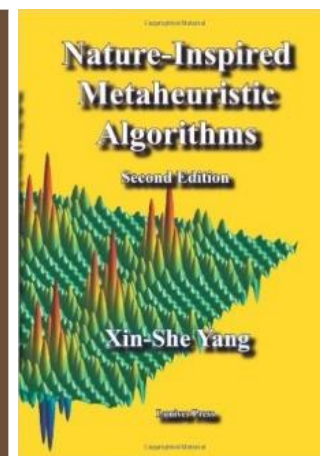
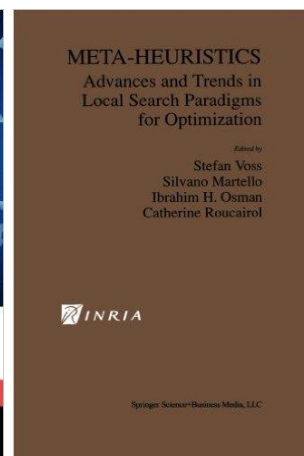
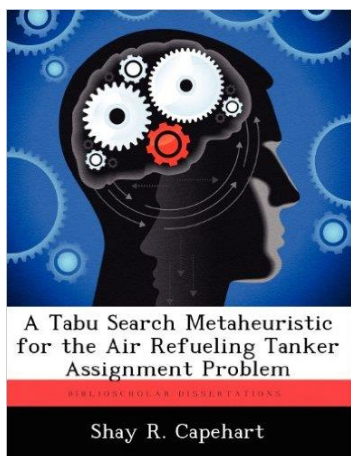
- QuickSort(X, i, j)
- MergeSort(X, i, j)

when either **stops**, **abort** the other

- **Ave-case** time is **Min** of both: $O(n \log n)$
- **Worst-case** time is **Min** of both: $O(n \log n)$
- Meta-algorithms / meta-heuristics **generalize!**



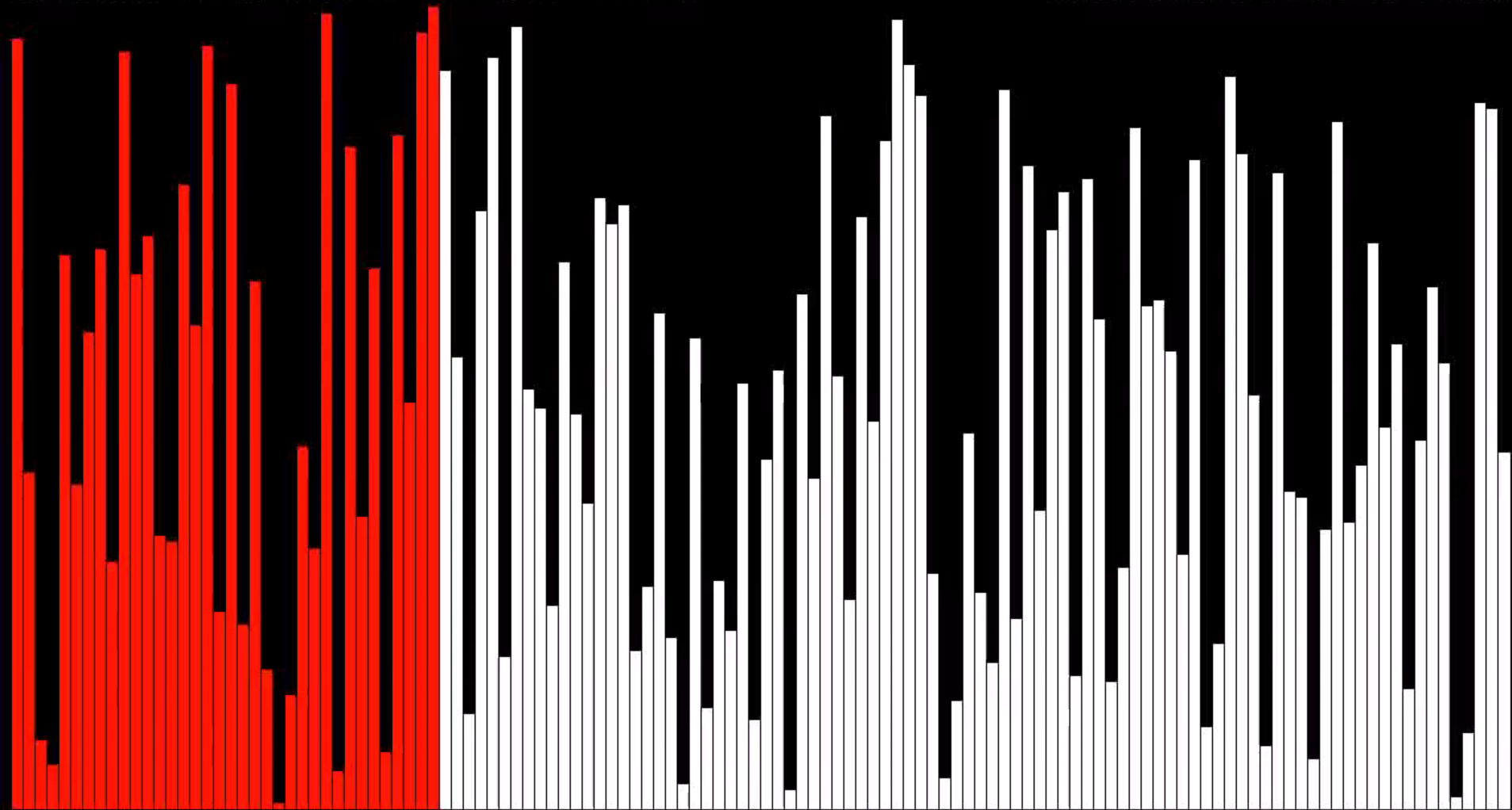




“The Sound of Sorting” (15 algorithms)

Selection Sort - 35 comparisons, 67 array accesses, 0.50 ms delay

<http://panthema.net/2013/sound-of-sorting>



- Sound **pitch** is proportional to **value** of current sort element sorted!

<https://www.youtube.com/watch?v=kPRA0W1kECg>

Problem: Given n pairs of integers (x_i, y_i) , where $0 \leq x_i \leq n$ and $1 \leq y_i \leq n$ for $1 \leq i \leq n$, find an algorithm that sorts all n ratios x_i / y_i in linear time $O(n)$.

- What approaches fail?
- What techniques work and why?
- Lessons and generalizations

Problem: Given n integers, find in $O(n)$ time the majority element (i.e., occurring $\geq n/2$ times, if any).

- What approaches fail?
- What techniques work and why?
- Lessons and generalizations

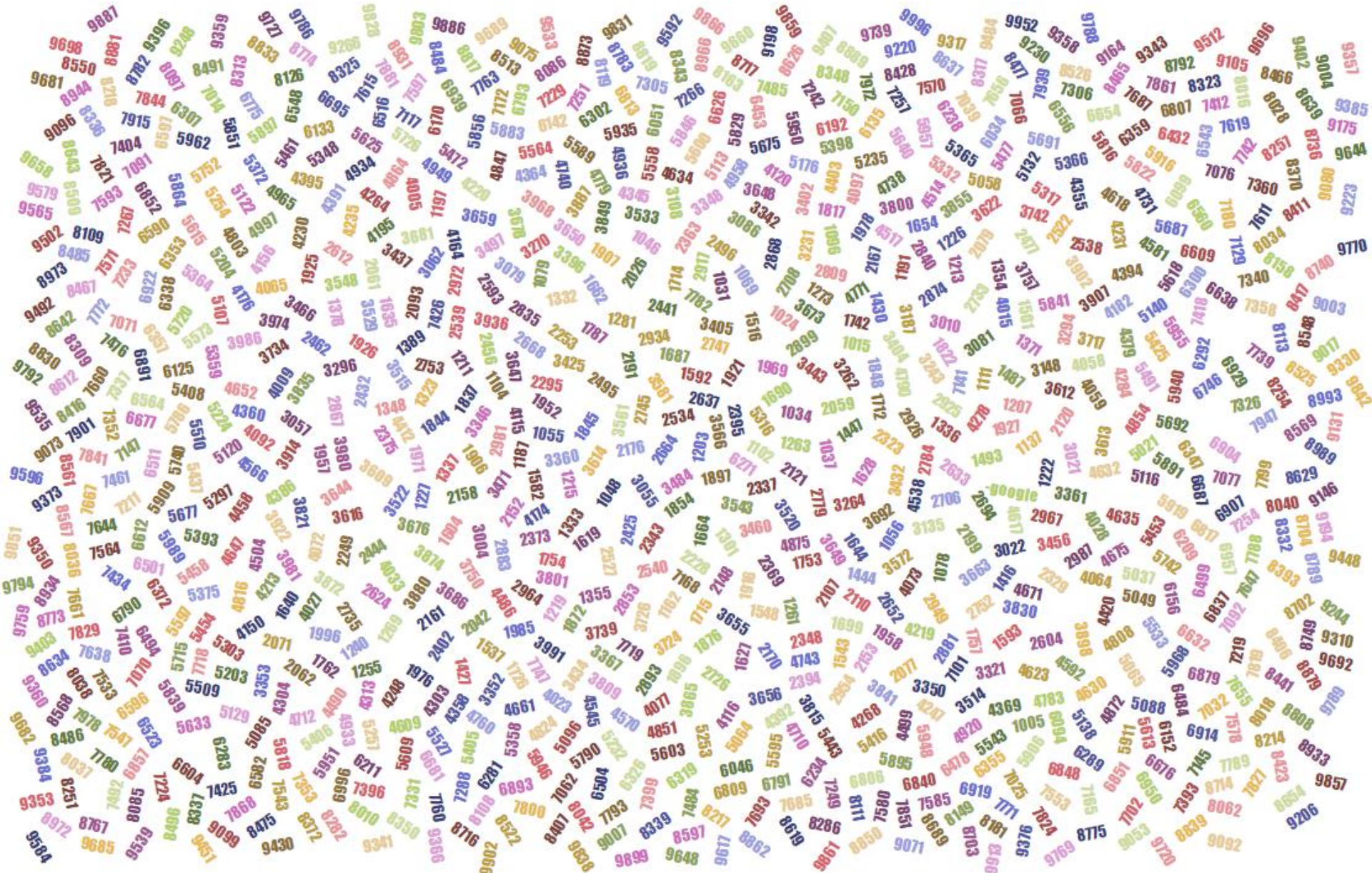
Problem: Given n objects, find in $O(n)$ time the **majority** element (i.e., occurring $\geq n/2$ times, if any), using only equality comparisons ($=$).

- What approaches fail?
- What techniques work and why?
- Lessons and generalizations

Problem: Given n integers, find both the **maximum** and the **next-to-maximum** using the least number of comparisons (**exact** comparison count, not just $O(n)$).

- What approaches fail?
- What techniques work and why?
- Lessons and generalizations

Finding the Minimum



Finding the Minimum

Input: array $X[1..n]$ of integers

Output: minimum element

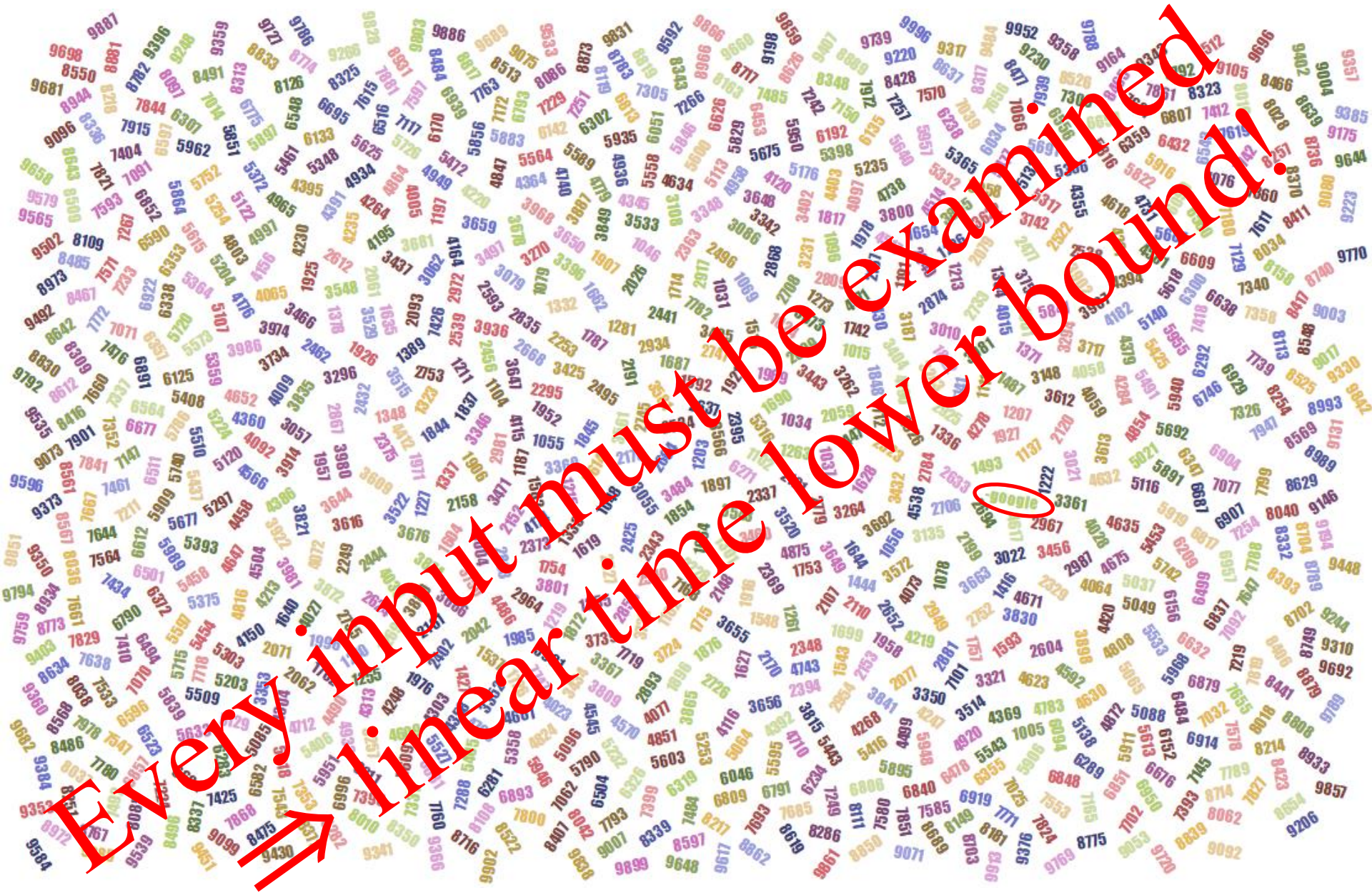
Theorem: $\Omega(n)$ time is necessary to find Min.

Proof 1: each element must be examined at least once, otherwise we may miss the true minimum. Therefore $\Omega(n)$ work is required.

Proof 2: Assume a correct min-finding algorithm didn't examine element X_i for some array X . Then the same algorithm will be wrong on X with X_i replaced with say -10^{100} .

Non-existence argument!
Proof by contradiction!

Finding the Minimum



Finding the Minimum

Input: array $X[1..n]$ of integers

Output: minimum element

Idea: keep track of the best-so-far

```
Min = X[1]
```

```
  for i = 2 to n
```

```
    if  $X[i] < \text{min}$  then  $\text{min} = X[i]$ 
```

- Exact comparison count: $n-1$

Theorem: $n-1$ comparisons are sufficient for finding the minimum.

Corollary: This $\Theta(n)$ -time algorithm is optimal.

Q: What about finding the maximum?

Finding the Minimum

Q: Can we do better than $n-1$ comparisons?

Theorem: $n/2$ comparisons are necessary for finding the **minimum**.

Idea: must examine all n inputs!

Proof: each element must participate in at least 1 comparison (otherwise we may miss e.g. -10^{100}).

- Each comparison involves 2 elements
- At least $n/2$ comparisons are necessary

Q: Can we improve **lower bound** up to $n-1$?

Non-existence proof!

Finding the Minimum

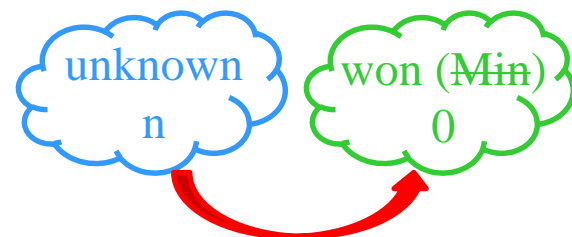
Theorem: $n-1$ comparisons are necessary for finding the minimum (or maximum).

Idea: keep track of “knowledge” gained!

Proof: consider two classes of elements:



Initial state:



Final state:



Every non-Min element must win at least once!

- At each comparison, at most 1 element moves from “unknown” to “won (Min)”.
- At least $n-1$ moves / comparisons are necessary to convert the initial state into the final state

Corollary: The $(n-1)$ -comparison algorithm is optimal.

Finding the Min and Max

Input: array $X[1..n]$ of integers

Output: **minimum** and **maximum** elements

Idea: find **Min** independently from **Max**

Find**Min**(X)

Find**Max**(X) \equiv Find**Min**($-X$)

- **n-1** comparisons to find **Min**
- **n-1** comparisons to find **Max**
- Total **2n-2** comparisons needed

Observation: much information is discarded!

Q: Can we do better than **2n-2** comparisons?

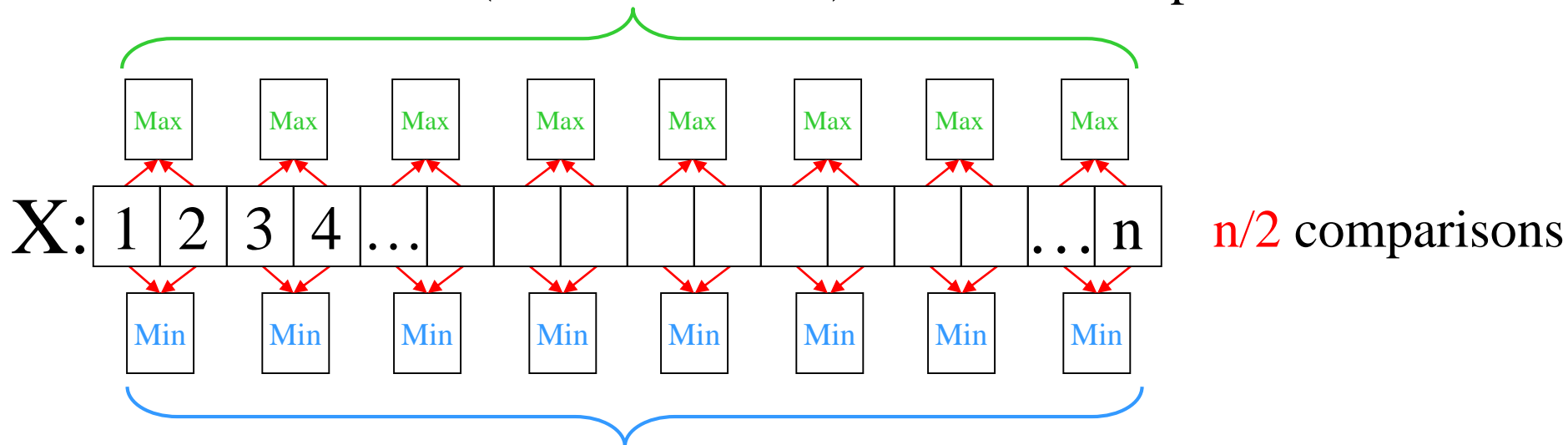
Finding the Min and Max

Input: array $X[1..n]$ of integers

Output: **minimum** and **maximum** elements

Idea: pairwise compare to reduce work

Max ($n/2$ **Max** values) $\Rightarrow n/2-1$ comparisons



Min ($n/2$ **Min** values) $\Rightarrow n/2-1$ comparisons

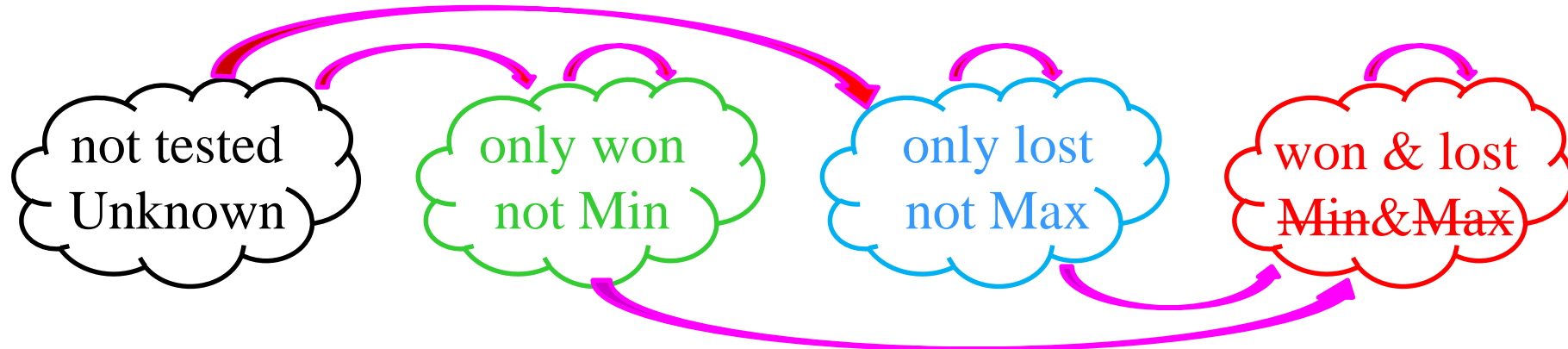
Theorem: $3n/2-2$ comparisons are **sufficient** for finding the **minimum** and **maximum**.

Finding the Min and Max

Theorem: $3n/2 - 2$ comparisons are **necessary** for finding the **minimum and maximum**.

Idea: keep track of “knowledge” gained!

Proof: consider four classes of elements:



Initial state:				
Final state:				
		Max	Min	

Finding the Min and Max

Not tested
unknown

only Won
not Min

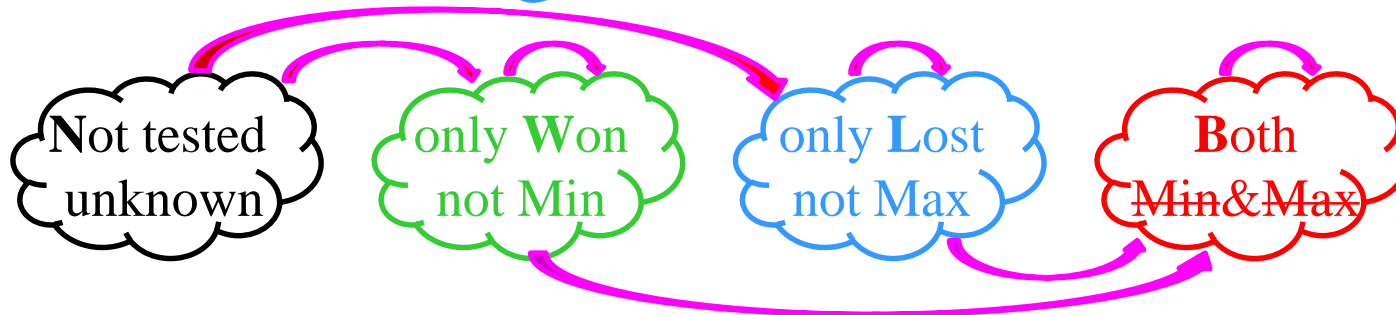
only Lost
not Max

Both
Min&Max

$N < N \Rightarrow L \& W$	$N > N \Rightarrow W \& L$	2
$N < W \Rightarrow L \& W$	$N > W \Rightarrow W \& B$	1
$N < L \Rightarrow L \& B$	$N > L \Rightarrow W \& L$	1
$N < B \Rightarrow L \& B$	$N > B \Rightarrow W \& B$	1
$W < W \Rightarrow B \& W$	$W > W \Rightarrow W \& B$	1
$W < L \Rightarrow B \& B$	$W > L \Rightarrow W \& L$	0
$W < B \Rightarrow B \& B$	$W > B \Rightarrow W \& B$	0
$L < L \Rightarrow L \& B$	$L > L \Rightarrow B \& L$	1
$L < B \Rightarrow L \& B$	$L > B \Rightarrow B \& B$	0
$B < B \Rightarrow B \& B$	$B > B \Rightarrow B \& B$	0

Minimum
guaranteed
knowledge
gained
i.e. “moves”
towards
final state

Finding the Min and Max



- Moving from **N** to **B** forces passing through **W** or **L**
 - Emptying **N** into **W** & **L** takes $n/2$ comparisons
 - Emptying most of **W** takes $n/2-1$ comparisons
 - Emptying most of **L** takes $n/2-1$ comparisons
 - Other moves will not reach the “final state” any faster
 - Total comparisons required: $3n/2-2$
- ⇒ $3n/2-2$ comparisons are necessary for finding the minimum and maximum.

Non-existence proof!

Theorem: Our **Min&Max** algorithm is optimal.

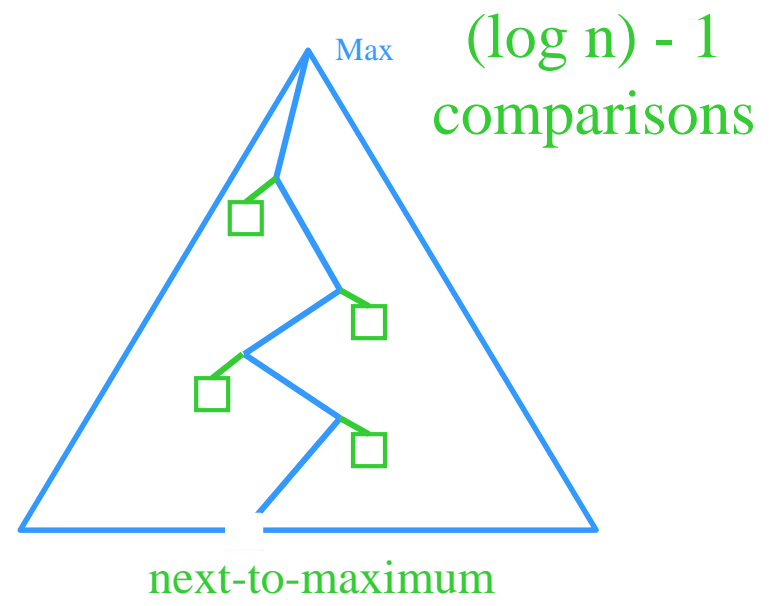
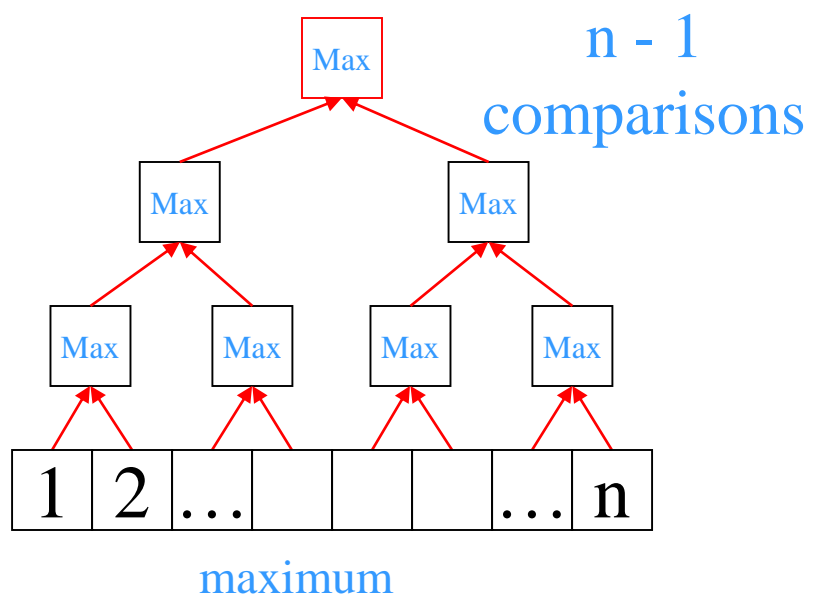
Problem: Given n integers, find both the **maximum** and the **next-to-maximum** using the least number of comparisons (**exact** comparison count, not just $O(n)$).

- What approaches fail?
- What techniques work and why?
- Lessons and generalizations

Finding the Max and Next-to-Max

Theorem: $(n-2) + \log n$ comparisons are sufficient for finding the maximum and next-to-maximum.

Proof: consider elimination tournament:



Theorem: $(n-2) + \log n$ comparisons are necessary for finding the maximum and next-to-maximum.

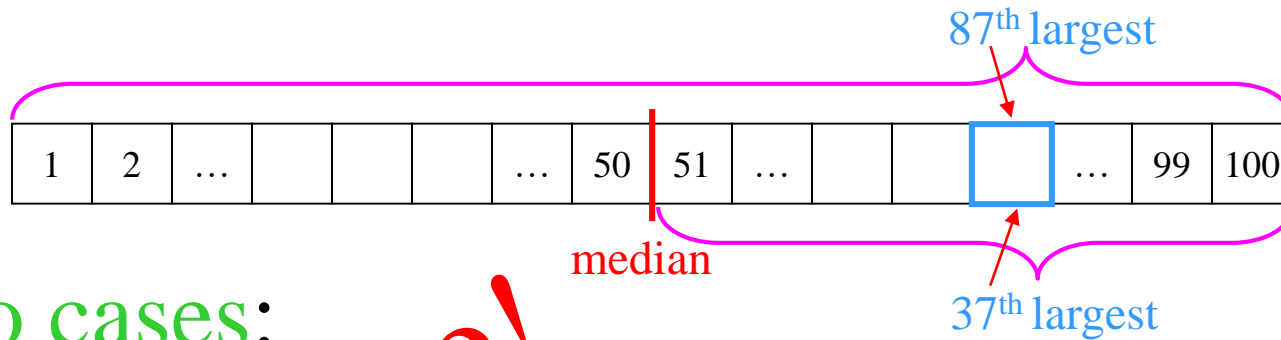
Selection (Order Statistics)

Input: array $X[1..n]$ of integers and i

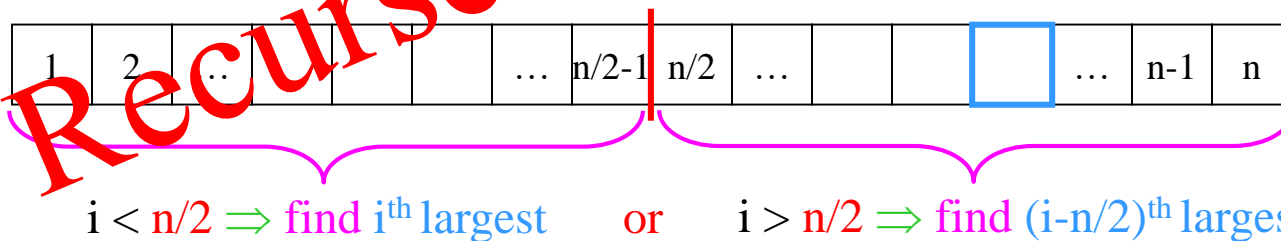
Output: i^{th} largest integer

Obvious: i^{th} -largest subroutine can find **median**
since **median** is the special case $(n/2)^{\text{th}}$ -largest

Not obvious: repeat **medians** can find i^{th} largest:



Two cases:



Recurse!

Selection (Order Statistics)

Run time for i^{th} largest: $T(n) = T(n/2) + M(n)$

where $M(n)$ is time to find **median**

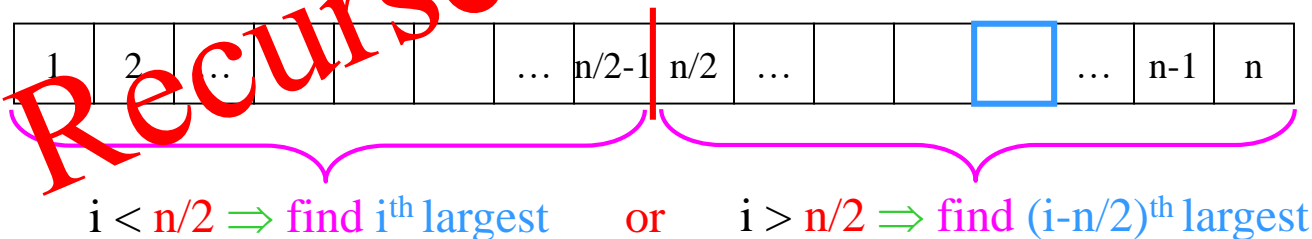
- Finding **median** in $O(n \log n)$ time is easy (**why?**)
- Assume $M(n) = c \cdot n = O(n)$

$$\begin{aligned} \Rightarrow T(n) &< c \cdot (n + n/2 + n/4 + n/8 + \dots) \\ &< c \cdot (2n) = O(n) \end{aligned}$$

Conclusion: linear-time **median** algorithm

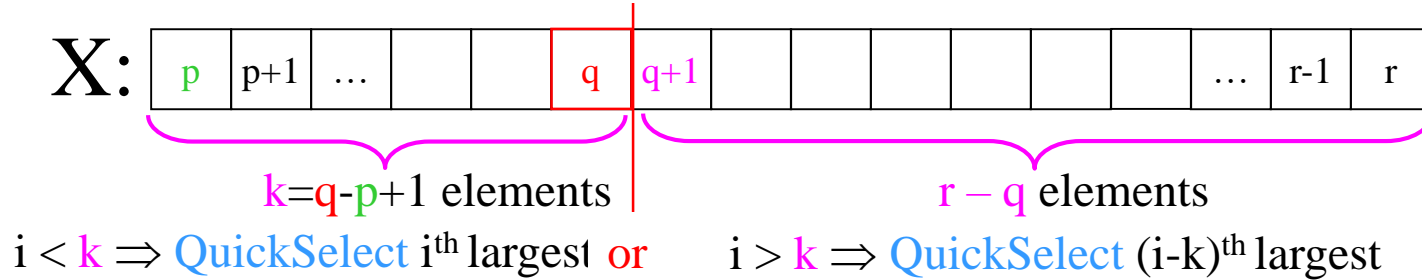
automatically yields linear-time i^{th} selection!

New goal: find the **median** in $O(n)$ time!



QuickSelect (i^{th} -Largest)

Idea: partition around pivot and recurse



QuickSelect(X, p, r, i)

if $p == r$ then return($X[p]$)

$q = \text{RandomPartition}(X, p, r)$

$k = q - p + 1$

If $i \leq k$ then return(**QuickSelect**(X, p, q, i))

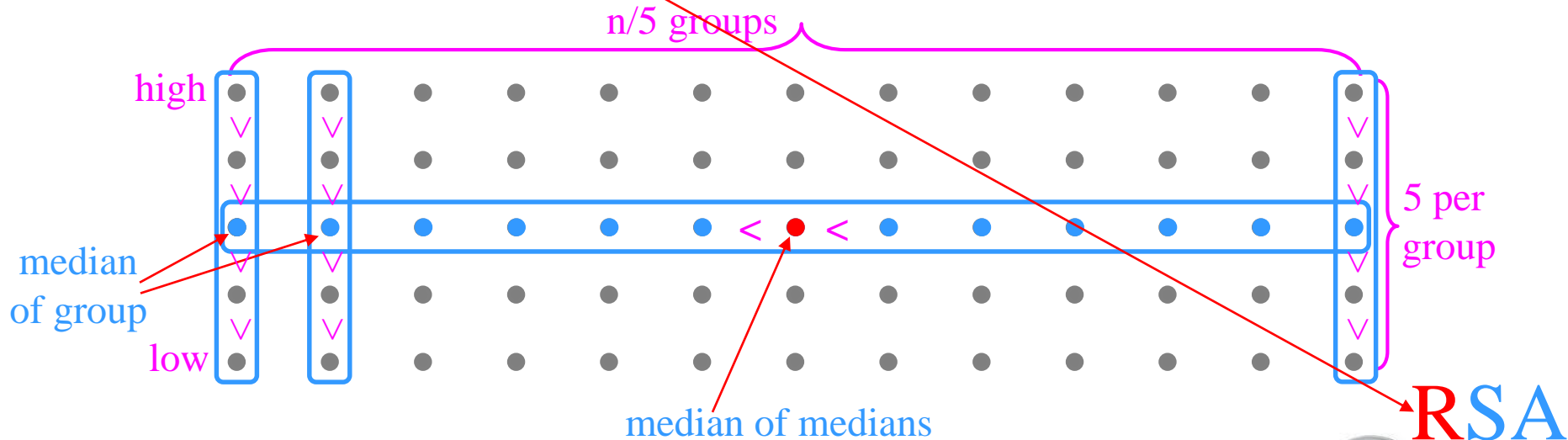
else return(**QuickSelect**($X, q+1, r, i-k$))

- $O(n)$ time **average**-case (analysis like QuickSort's)
- $\Theta(n^2)$ worst-case time (very rare)

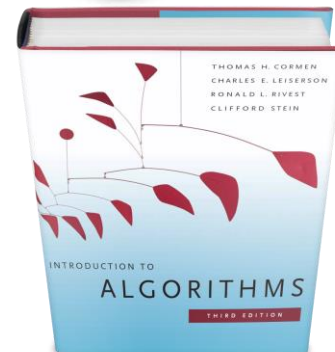
Median in Linear Time

Idea: quickly eliminate a constant fraction & repeat

[Blum, Floyd, Pratt, **Rivest**, and Tarjan, 1973]



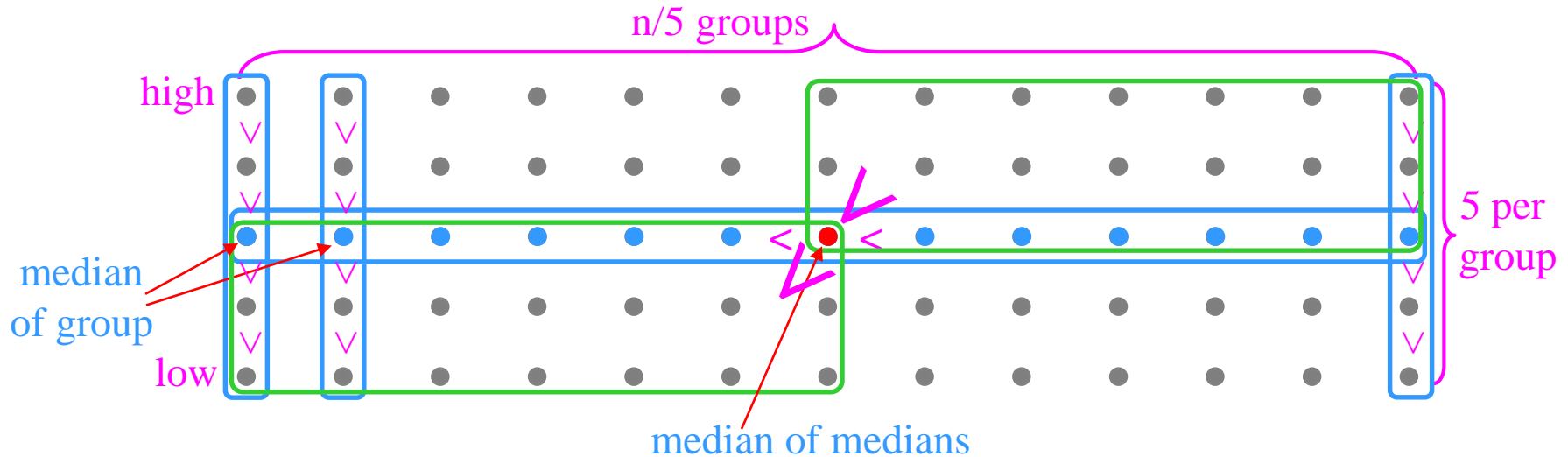
- Partition into $n/5$ groups of 5 each
- Sort each group (high to low)
- Compute **median of medians** (recursively)
- Move columns with larger medians to right
- Move columns with smaller medians to left



Median in Linear Time

Idea: quickly eliminate a constant fraction & repeat

[Blum, Floyd, Pratt, Rivest, and Tarjan, 1973]

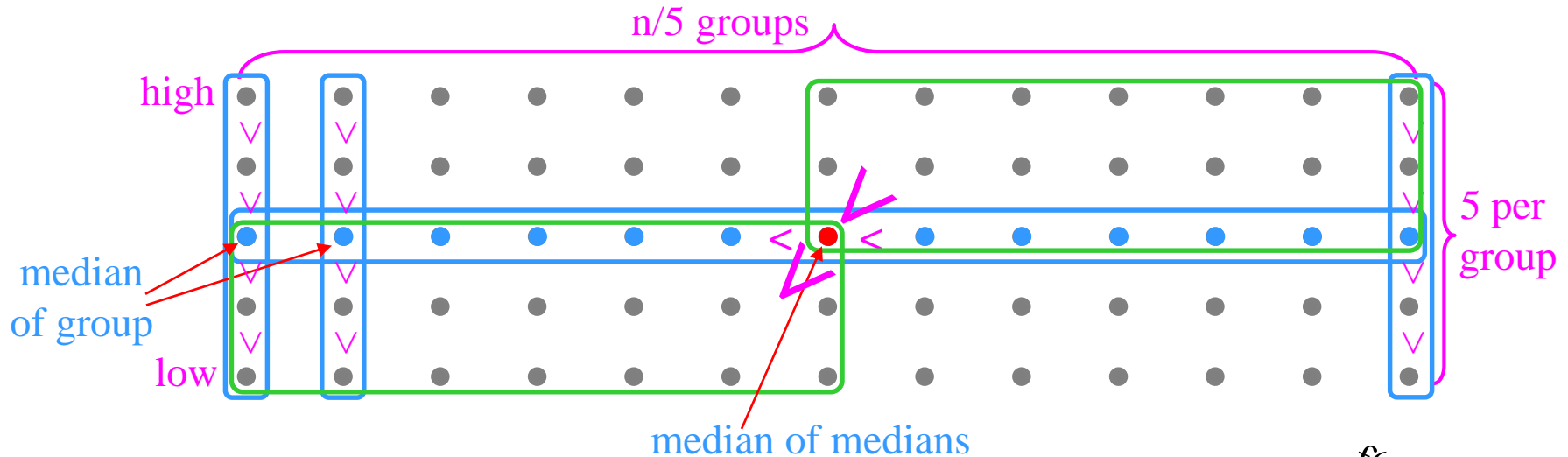


- $> 3/10$ of elements larger than **median of medians**
- $> 3/10$ of elements smaller than **median of medians**
- Partition all elements around **median of medians**
- Each partition contains **at most $7n/10$** elements
- **Recurse** on the proper partition (like in **QuickSelect**)

Median in Linear Time

Idea: quickly eliminate a constant fraction & repeat

[Blum, Floyd, Pratt, Rivest, and Tarjan, 1973]



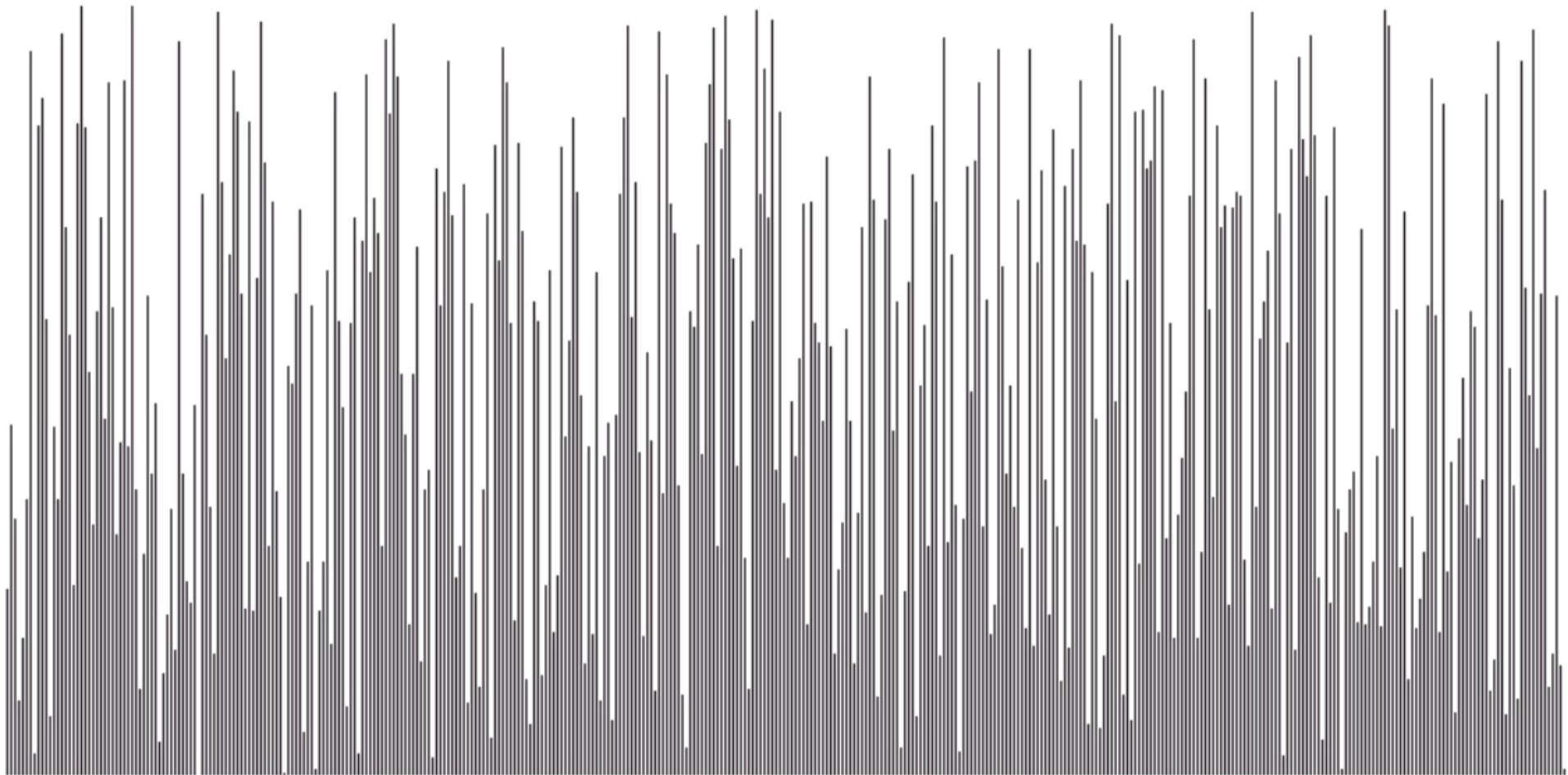
$$\begin{aligned}
 T(n) &= T(n/5) + T(7n/10) + O(n) \\
 &= T(2n/10) + T(7n/10) + O(n) \\
 &\leq T(2n/10 + 7n/10) + O(n) \text{ since } T(n) = \Omega(n) \\
 &= T(9n/10) + O(n) \Rightarrow T(n) = O(n)
 \end{aligned}$$

$$\begin{aligned}
 f(n) &= \Omega(n) \Rightarrow \\
 f(x+y) &\geq f(x) + f(y)
 \end{aligned}$$

Large constant Overhead!

- **Median** is found in $\Theta(n)$ time worst-case!

Median in Linear Time



Exact upper bounds: $< 24n, 5.4n, 3n, 2.95n, \dots + o(n)$

Exact lower bounds: $> 1.5n, 1.75n, 1.8n, 1.837n, 2n, \dots + O(1)$

Closing this comparisons gap further is still an open problem!