## k-Selection; Median

- Select the k-th smallest item in the list
- Naïve Solution
- Sort:
- pick the k-th smallest item in sorted list.
$O(n \log n)$ time complexity
- Randomized solution: Average case O(n)
- Improved Solution: worst case O(n)

```
QuickSort(A, \(\mathrm{p}, \mathrm{r}\) )
    if \((p<r)\) then
        \(\mathrm{q}=\operatorname{Partition(A,p,r)}\)
        QuickSort(A, p, q)
        QuickSort(A, 1+1, r)
\(\operatorname{Partition}(A, p, r)\)
    \(\mathrm{x}=\mathrm{A}[\mathrm{p}]\)
    \(\mathrm{i}=\mathrm{p}-1\)
    \(\mathrm{j}=\mathrm{r}+1\)
    while TRUE do
    repeat
        j- -
    until ( \(\mathrm{A}[\mathrm{j}]<=\mathrm{x}\) )
        repeat
        i++
    until ( \(\mathrm{A}[\mathrm{i}]>=\mathrm{x}\) )
    if \((\mathrm{i}<\mathrm{j}) \operatorname{SWAP}(\mathrm{A}[\mathrm{i}], \mathrm{A}[\mathrm{j}])\)
    else return j
```


## Partition Procedure Revisited

- The Partition code can be rewritten so that it accepts another parameter, namely, the pivot value. Let's call this new variation as PivotPartition.
- This change does not affect its time complexity.
- RandomizedPartition as used in RandomizedSelect picks the pivot uniformly at random from among the elements in the list to be partitioned.


## Randomized Selection

RandomizedSelect( $A, p, r, i)$

$$
\text { if }(p=r) \text { then }
$$

return A[p]
$q=$ RandomizedPartition(A, $p, r$ )
$k=q-p+1$
if ( $i<=k$ )
return RandomizedSelect(A, p, q, i)
else
return RandomizedSelect( $A, q+1, r, i-k)$

## Randomized Selection: Rewritten

RandomizedSelect(A, $p, r, i)$

$$
\text { if }(p=r) \text { then }
$$

return $A[p]$
Pivot $=A[\operatorname{random}(p, r)]$
$q=$ PivotPartition(A, $p, r$, Pivot)
$k=q-p+1$
if ( $i \ll k$ )
return RandomizedSelect(A, p, q, i)
else
return RandomizedSelect( $A, q+1, r, i-k)$

## k-Selection \& Median: Improved Algorithm

- Start with initial array



## k-Selection \& Median: Improved Algorithm(Cont'd)

- Use median of medians as pivo†

- $T(n)<O(n)+T(n / 5)+T(3 n / 4)$


## Improved Selection

```
ImprovedSelect( \(A, p, r, i)\)
    if \((p=r)\) then
        return \(A[p]\)
        else \(N=r-p+1\)
        Partition \(A[p . . r]\) into subsets of 5 elements and collect all
        the medians of the subsets in \(\mathrm{B}[1 . .(\mathrm{N} / 5)\) ].
        Pivot = ImprovedSelect ( \(B, 1,\lceil N / 5\rceil,\lceil N / 10\rceil\) )
    \(q=\) PivotPartition (A, p, r, Pivot)
    \(k=q-p+1\)
    if ( \(i<=k\) )
        return ImprovedSelect(A, p, q, i)
    else
    return ImprovedSelect( \(A, q+1, r, i-k)\)
```


## Upper \& Lower Bounds

- Algorithm A solves problem P if it terminates \& gives the correct output on every possible input.
- Algorithm A solving problem $P$ has time complexity $f(n)$ if it takes time at most $f(n)$ for every input of length $n$.
- $U(n)$ is an upper bound on the time complexity of $P$, if there exists an algorithm $A$ that solves $P$ and has time complexity $U(n)$.
- $L(n)$ is a lower bound on the time complexity of $P$, if there exists NO algorithm that solves $P$ and has time complexity asymptotically less than $L(n)$.


## Upper \& Lower Bounds for Maximum

- Naïve Algorithm A solves the Maximum problem, because it terminates in $n$ iterations for every possible input of length $n$ and outputs the correct maximum.
- Naïve Algorithm A has time complexity $O(n)$.
- $O(n)$ is an upper bound on the time complexity of the maximum problem.
- $(n-1)$ is a lower bound on the time complexity of the maximum problem, because there exists NO algorithm that solves it with less than n-1 comparisons.
- WHY? In 1 comparison, at most 1 item is eliminated from being the maximum. How many to eliminate?
- Therefore, no matter how smart you are you cannot design an algorithm that solves the Maximum problem in less than $n-1$ comparisons on all inputs of length $n$.


## Upper Bound on Sorting n items

- $O(n \log n)$ is the upper bound for sorting.
- WHY?
- HeapSort
- MergeSort
- What about QuickSort?
- $O\left(n^{2}\right)$ in the worst case!


## Lower Bound for Sorting: Decision Tree Model

- The decision tree model models all comparison-based algorithms that solve the sorting problem. These algorithms perform no other "algebraic" operations on input values.
They may perform data movements \& other statements.
- Imagine a binary tree that models the algorithm, where
- each node corresponds to a comparison
- the edges to the children correspond to the two outcomes of the comparison: YES/NO
- Leaves correspond to the output. WHAT IS THE OUTPUT?
- Decision tree for InsertionSort on 4 items?
- What can we say about such decision trees?
- Given an input, the algorithm follows a path from the root to a leaf.


## Lower Bound for Sorting: Cont'd

- Leaves correspond to outputs.
- Paths correspond to a path followed on a specific input. Time complexity = height of decision tree.
- Different input orders must force different paths or else the output will end up being the same, giving rise to incorrect sorted orders.
- Therefore number of leaves is at least as large as the number of different input orders.
- HOW MANY?
- n!
- Height of the decision tree is at least $\log (n!)$. Hence lower bound is $O(\log (n!))=O(n \log n)$

