

# COMP251: Probabilistic analysis

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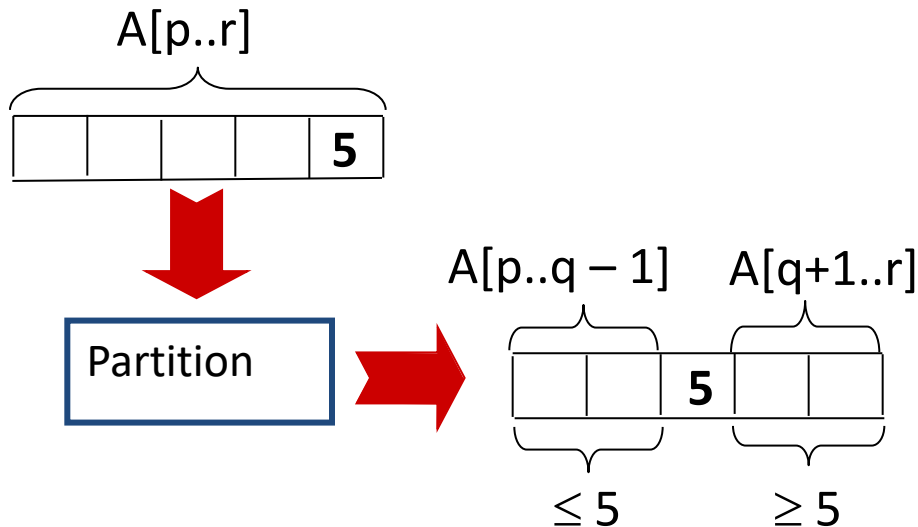
Based on slides from Lin & Devi (UNC)

# **Review of Quicksort**

# QuickSort: Review

Quicksort(A, p, r)

```
if  $p < r$  then  
     $q := \text{Partition}(A, p, r);$   
    Quicksort(A, p,  $q - 1$ );  
    Quicksort(A,  $q + 1$ , r)  
fi
```

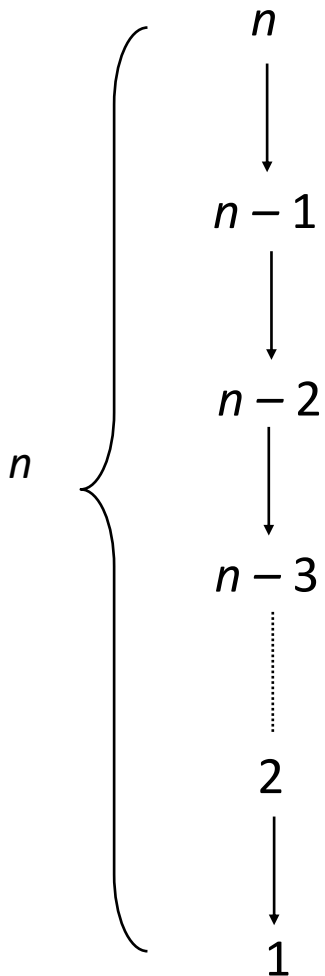


Partition(A, p, r)

```
 $x, i := A[r], p - 1;$   
for  $j := p$  to  $r - 1$  do  
    if  $A[j] \leq x$  then  
         $i := i + 1;$   
         $A[i] \leftrightarrow A[j]$   
    fi  
od;  
 $A[i + 1] \leftrightarrow A[r];$   
return  $i + 1$ 
```

# Worst-case Partition Analysis

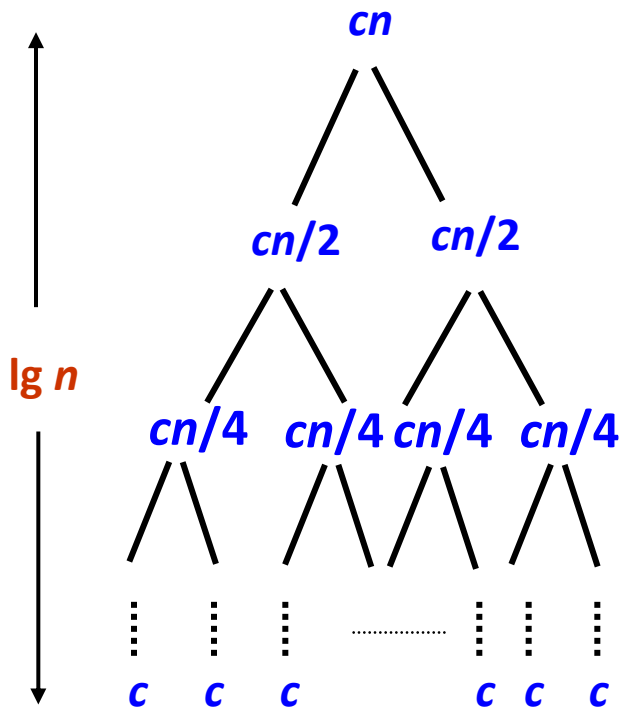
Recursion tree for  
worst-case partition



Split off a single element at each level:

$$\begin{aligned} T(n) &= T(n-1) + T(0) + \text{PartitionTime}(n) \\ &= T(n-1) + \Theta(n) \\ &= \sum_{k=1 \text{ to } n} \Theta(k) \\ &= \Theta\left(\sum_{k=1 \text{ to } n} k\right) \\ &= \Theta(n^2) \end{aligned}$$

# Best-case Partitioning



- Each subproblem size  $\leq n/2$ .
- Recurrence for running time
  - $T(n) \leq 2T(n/2) + \text{PartitionTime}(n)$   
 $= 2T(n/2) + \Theta(n)$
- $T(n) = \Theta(n \lg n)$

# Variations

- Quicksort is not very efficient on small lists.
- This is a problem because Quicksort will be called on lots of small lists.
- **Fix 1:** Use Insertion Sort on small problems.
- **Fix 2:** Leave small problems unsorted. Fix with one final Insertion Sort at end.

**Why?** Insertion Sort is very fast on almost-sorted lists.

# **Average case analysis**

# Unbalanced Partition Analysis

What happens if we get poorly-balanced partitions,

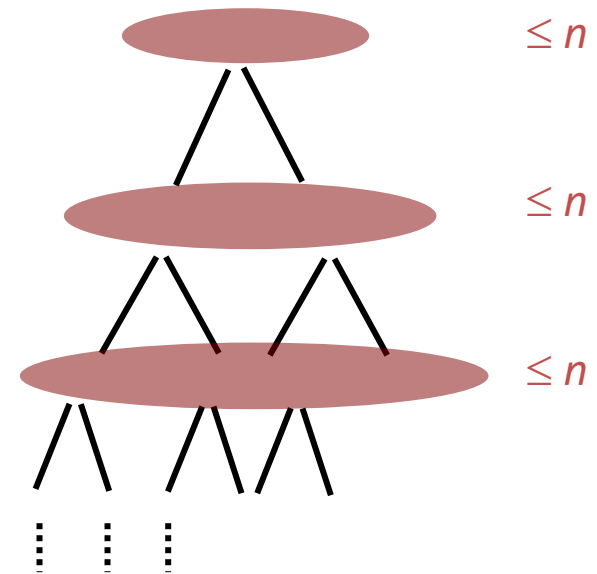
e.g., something like:  $T(n) \leq T(9n/10) + T(n/10) + \Theta(n)$ ?

Still get  $\Theta(n \lg n)$ !! (As long as the split is of constant proportionality)

**Intuition:** Can divide  $n$  by  $c > 1$  only  $\Theta(\lg n)$  times before getting 1.

$n$   
↓  
 $n/c$   
↓  
 $n/c^2$   
↓  
⋮  
↓  
 $1 = n/c^{\log_c n}$

Roughly  $\log_c n$  levels;  
Cost per level is  $O(n)$ .



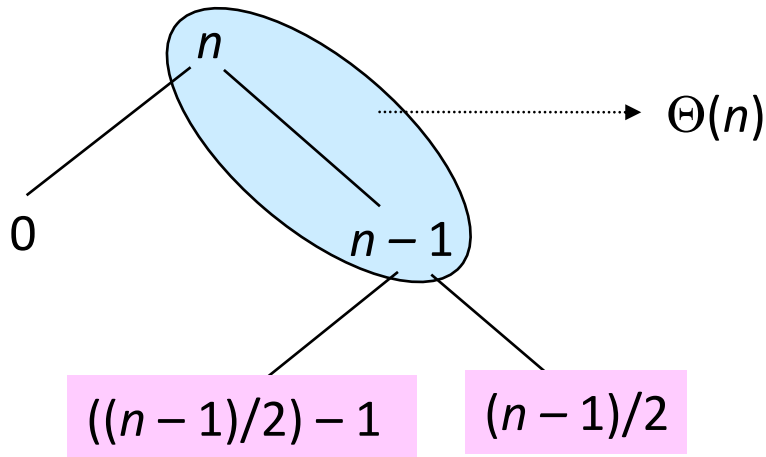
Note: Different base logs are related by a constant.

# Intuition for the Average Case

- Partitioning is unlikely to happen in the same way at every level.
  - Split ratio is different for different levels.  
(Contrary to our assumption in the previous slide.)
- Partition produces a mix of “good” and “bad” splits, distributed randomly in the recursion tree.

**What is the running time likely to be in such a case?**

# Intuition for the average case

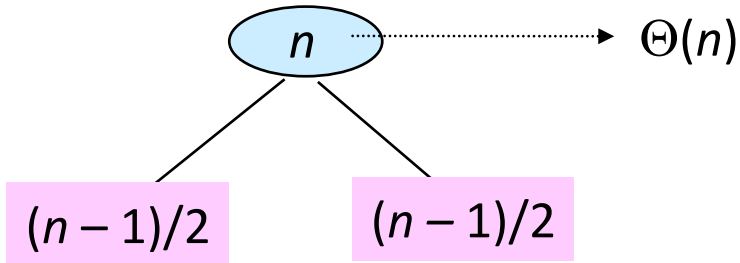


Bad split followed by a good split:

Produces subarrays of sizes  $0$ ,  $(n-1)/2 - 1$ , and  $(n-1)/2$ .

Cost of partitioning :

$$\Theta(n) + \Theta(n-1) = \Theta(n).$$



Good split at the first level:

Produces two subarrays of size  $(n-1)/2$ .

Cost of partitioning :

$$\Theta(n).$$

Situation at the end of case 1 is not worse than that at the end of case 2.

When splits alternate between good and bad, the **cost of bad split can be absorbed into the cost of good split.**

Thus, the running time is  $O(n \lg n)$ , though with larger hidden constants.

# **Randomized quicksort**

# Randomized Quicksort

- ♦ Want to make running time independent of input ordering.
- ♦ How can we do that?
  - » Make the algorithm randomized.
  - » Make every possible input equally likely.
    - Can randomly shuffle to permute the entire array.
    - For quicksort, it is sufficient if we can ensure that every element is equally likely to be the *pivot*.
    - So, we choose an element in  $A[p..r]$  and exchange it with  $A[r]$ .
    - Because the *pivot* is randomly chosen, we expect the partitioning to be well balanced on average.

# Variations (Continued)

- Input distribution may not be uniformly random.
- **Fix 1:** Use “randomly” selected pivot.
  - We will analyze this in detail.
- **Fix 2:** Median-of-three Quicksort.
  - Use median of three fixed elements (say, the first, middle, and last) as the pivot.
  - To get  $O(n^2)$  behavior, we must continually be unlucky to see that two out of the three elements examined are among the largest or smallest of their sets.

# Randomized Version

Want to make running time independent of input ordering.

```
Randomized-Partition(A, p, r)
```

```
  i := Random(p, r);
```

```
  A[r]  $\leftrightarrow$  A[i];
```

```
  return Partition(A, p, r)
```

```
Randomized-Quicksort(A, p, r)
```

```
  if p < r then
```

```
    q := Randomized-Partition(A, p, r);
```

```
    Randomized-Quicksort(A, p, q - 1);
```

```
    Randomized-Quicksort(A, q + 1, r)
```

```
  fi
```

**Average case analysis**

# Average Case Analysis of **Randomized Quicksort**

Random Variable  $X$  = # comparisons over all calls to Partition.

Why is it a good measure? Intuition: there are at most  $n$  calls to Partition. The running time of these calls is upper bounded by the number of comparisons.

## Notation:

- Let  $z_1, z_2, \dots, z_n$  denote the list items (in sorted order).
- Let  $Z_{ij} = \{z_i, z_{i+1}, \dots, z_j\}$ .

Let RV  $X_{ij} = \begin{cases} 1 & \text{if } z_i \text{ is compared to } z_j \\ 0 & \text{otherwise} \end{cases}$

$X_{ij}$  is an **indicator random variable**.  
 $X_{ij} = I\{z_i \text{ is compared to } z_j\}.$

Thus, 
$$X = \sum_{i=1}^{n-1} \sum_{j=i+1}^n X_{ij}.$$

# Analysis (Continued)

We have:

$$E[X] = E\left[\sum_{i=1}^{n-1} \sum_{j=i+1}^n X_{ij}\right]$$

$$= \sum_{i=1}^{n-1} \sum_{j=i+1}^n E[X_{ij}]$$

$$= \sum_{i=1}^{n-1} \sum_{j=i+1}^n P[z_i \text{ is compared to } z_j]$$

**Reminder:**

$$\begin{aligned} E[X_{ij}] &= 0 \cdot P[X_{ij}=0] + 1 \cdot P[X_{ij}=1] \\ &= P[X_{ij}=1] \end{aligned}$$

So, all we need to do is to compute  $P[z_i \text{ is compared to } z_j]$ .

# Analysis (Continued)

**Claim:**  $z_i$  and  $z_j$  are compared iff the first element to be chosen as a pivot from  $Z_{ij}$  is either  $z_i$  or  $z_j$ .

Hint: what happens if an element in  $Z_{ij}$  other than  $z_i$  or  $z_j$  is chosen as pivot first?

**Exercise:** Prove this.

$$\begin{aligned}\text{So, } P[z_i \text{ is compared to } z_j] &= P[z_i \text{ or } z_j \text{ is first pivot from } Z_{ij}] \\ &= P[z_i \text{ is first pivot from } Z_{ij}] \\ &\quad + P[z_j \text{ is first pivot from } Z_{ij}]\end{aligned}$$

We choose the pivot uniformly at random

$$= \frac{1}{j-i+1} + \frac{1}{j-i+1}$$

$$= \frac{2}{j-i+1}$$

# Analysis (Continued)

Therefore,

$$E[X] = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \frac{2}{j-i+1}$$

$$= \sum_{i=1}^{n-1} \sum_{k=1}^{n-i} \frac{2}{k+1}$$

$$< \sum_{i=1}^{n-1} \sum_{k=1}^n \frac{2}{k}$$

Substitute  $k = j - i$ .

$$= \sum_{i=1}^{n-1} O(\lg n)$$

$$= O(n \lg n).$$

$$\sum_{k=1}^n \frac{1}{k} = H_n$$

$H_n = \ln n + O(1)$   
( $n^{\text{th}}$  Harmonic number)

# Deterministic vs. Randomized Algorithms

- **Deterministic Algorithm** : Identical behavior for different runs for a given input.
- **Randomized Algorithm** : Behavior is generally different for different runs for a given input.

