



Algorithms and Data Structures

Sorting:

Simple Methods and a Lower Bound

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This Course

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Large-Scale Sorting

- Imagine you are the IT head of a telco-company
- You have 30.000.000 customers each performing ~ 100 telephone calls per months, each call creating 200 bytes
 - That's $30M * 100 * 12 * 200 = 7.200.000.000.000$ bytes per year
 - Somewhere in the 200 bytes is information on revenue per call
 - Imagine the data is in one file, **one line per call**
- At the end of the year, management wants a list of all customers with **aggregated revenue per day** (for one year)
 - That's $\sim 30M * 12 * 30 \sim 10.000.000.000$ real numbers
- Problem: How can we compute these $10E9$ numbers?

Approach 0a: Load into Memory and Scan

- This **won't work**
- Data is too big to be loaded into main memory

Approach 0b: Load into a DBMS and use SQL

- This will work
- Not topic of our lecture

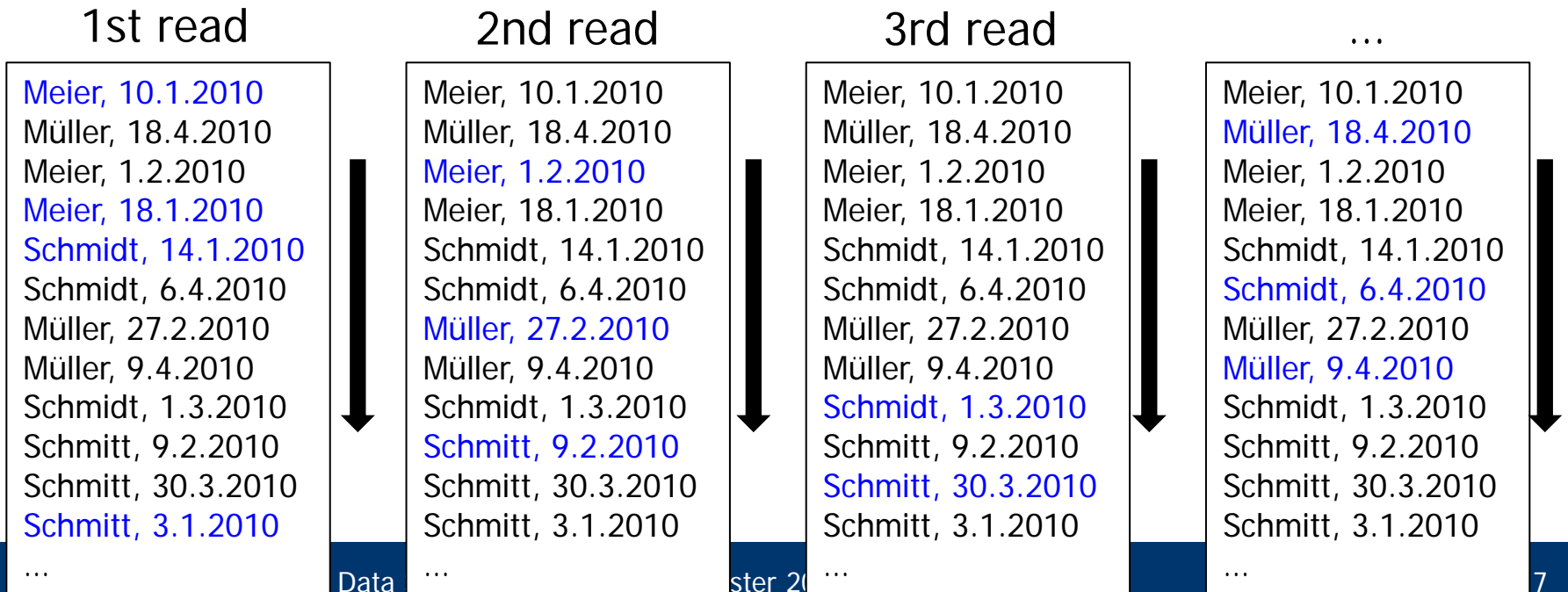
- [Will be slow – inserting is costly]
- [DBMS will use the same trick we present right now]

Approach 1: Scan and Keep Intermediate Results

- Eventually, we need $10E9$ real numbers
- Scan the file from start to end
 - Build a table (how?) on every combination of customer and day
 - When reading a record, **look-up combination in table** and update
- That's fast (if the table-look-up is fast)
- But we need $\sim 64\text{GB}$
- What if want the sum for each day over 10 years?
- This **won't scale**

Approach 2: Partition Data, Multiple Reads

- Assume we can keep $30M \times 30 \sim 1E9$ numbers in memory
 - Solve the problem month-by-month
 - Read the **call-file 12 times**, each time computing aggregates for all customers and the days of **one month**
 - This will **be slow**



Approach 3: Sorting

- Alternative?
 - Sort the file **by customer and day**
 - Read **sorted file once** and compute aggregates on the fly
 - Whenever a pair (day, customer) is finished (i.e., new values appear), sum can be written out and next day/customer starts
 - This will be **very fast**
 - Needs virtually **no memory** during counting
- But: Can we **sort ~3 billion records** using less than 12 reads?

Meier, 10.1.2010	
Meier, 10.1.2010	→ Sum
Meier, 1.2.2010	→ Sum
Müller, 27.2.2010	→ Sum
Müller, 9.4.2010	
Müller, 9.4.2010	→ Sum
Schmidt, 14.1.2010	...
Schmidt, 1.3.2010	
Schmidt, 6.4.2010	
Schmitt, 3.1.2010	
Schmitt, 3.1.2010	
Schmitt, 30.3.2010	
...	

Content of this Lecture

- **Sorting**
- Simple Methods
- Lower Bound

Sorting

- Assumptions
 - We have n values (integer, called keys) that should be sorted
 - Values are stored in **an array S** (i.e., $O(1)$ access to i 'th element)
 - Comparing two values costs $O(1)$
 - We usually **count # of comparisons**; sometimes also # of swaps
 - Values are not interpreted
 - We do not know what a “big” value is or how many percent of all values are smaller than a given value or ...
 - All we can do is **compare two values**
- We seek a **permutation π of the indexes** of S such that
$$\forall i, j \leq n \text{ with } \pi(i) < \pi(j) : S[\pi(i)] \leq S[\pi(j)]$$

Variations

- External versus **internal sorting**
 - Internal sorting: S fits into **main memory**
 - External sorting: There are too many records to fit in memory
 - We only look at internal sorting (see DB lecture)
- **In-place** or with additional memory
 - In-place sorting only requires a constant (independent of n) amount of **additional** memory (on top of S)
 - We will look at both
- Pre-Sorting
 - Some algorithms can take advantage of an existing (incomplete, erroneous) **order in the data**, some not
 - We will not exploit pre-sorting

Applications

- Sorting is a **ubiquitous** task in computer science
 - [OW93] claims that 25% of all computing time is spent in sorting
- Second example: Information Retrieval
 - Imagine you want to build $g^{*****}++$
 - Fundamental operation: In a very large set of documents, find those that contain a given **set of keywords**
 - [Note: That's not what a search engine does!]
 - Popular way of doing this: Build an **inverted index**

Inverted Index

ID	Text
1	Baseball is played during summer months.
2	Summer is the time for picnics here.
3	Months later we found out why.
4	Why is summer so hot here?

Term	Freq	Document ids
baseball	1	[1]
during	1	[1]
found	1	[3]
here	2	[2], [4]
hot	1	[4]
is	3	[1], [2], [4]
months	2	[1], [3]
summer	3	[1], [2], [4]
the	1	[2]
why	2	[3], [4]

Source: <http://docs.lucidworks.com>

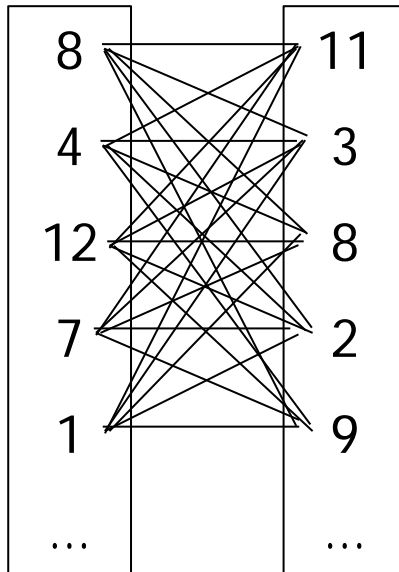
Answering a IR-style Query

- A **query** is a set of keywords
- Finding the answer
 - For each keyword k_i of the query, load **list d_i of docs containing k_i** from inverted index
 - Build **intersection of all d_i**
 - Docs in this list are your answer
- Imagine the query “the man eats a bread” on the Web
 - Doc-list for “the” and “a” will contain >10 billion documents
- How do we compute the **intersection of two sets** of 10 billion IDs?

Intersection of Two Sets

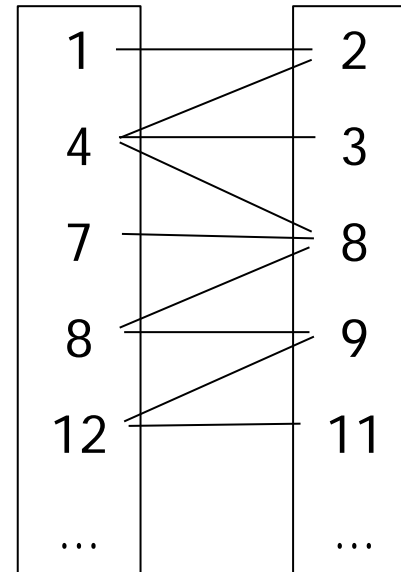
With non-sorted sets:

$$O(m \cdot n)$$



With sorted sets:

$$O(n+m)$$



Content of this Lecture

- Sorting
- Simple Methods
 - Selection sort
 - Insertion sort
 - Bubble sort
- Lower Bound

Recall: Selection Sort

```
S: array_of_names;
n := |S|
for i = 1..n-1 do
  for j = i+1..n do
    if S[i]>S[j] then
      tmp := S[j];
      S[j] := S[i];
      S[i] := tmp;
    end if;
  end for;
end for;
```

- Analysis showed that selection sort is in $O(n^2)$
- It is easy to see that selection sort also is in $\Omega(n^2)$
- How often do we **swap values**?
 - That depends a lot on the pre-sorted'ness of the array
 - But actually we can do a bit better

Selection Sort Improved

```
S: array_of_names;
n := |S|
for i = 1..n-1 do
  min_pos := i;
  for j = i+1..n do
    if S[min_pos]>S[j] then
      min_pos := j;
    end if;
  end for;
  if min_pos != i then
    tmp := S[i];
    S[i] := S[min_pos];
    S[min_pos] := tmp;
  end if;
end for;
```

- How often do we swap values?
 - Once for every position
 - Thus: $O(n)$ swaps
 - But more (cheaper) assignments

Analogy

- Let's assume you keep your cards sorted
- How to get this order?
 - Selection sort: Take up all cards at once and build **sorted prefixes** of increasing length
 - Insertion sort: Take up cards one by one and **sort every new card** into the sorted subset in your hand
 - Bubble sort: Take up all cards at once and **swap neighbors** until everything is fine



Insertion Sort

```
S: array_of_names;
n := |S|
for i = 2..n do
  j := i;
  key := S[j];
  while (S[j-1]>key) and (j>1) do
    S[j] := S[j-1];
    j := j-1;
  end while;
  S[j] := key;
end for;
```

- After each loop of i , the prefix $S[1..i]$ of S is sorted
- While-loop runs backwards from current position (to be inserted) until **values get too small (smaller than $S[j]$)**
- Example: 5 4 8 1 6
- One problem is the required **movement of many values** until correct place is found
 - Could be implemented much better with a **double-linked list**

Complexity (Worst Case)

```
S: array_of_names;
n := |S|
for i = 2..n do
  j := i;
  key := S[j];
  while (S[j-1]>key) and (j>1) do
    S[j] := S[j-1];
    j := j-1;
  end while;
  S[j] := key;
end for;
```

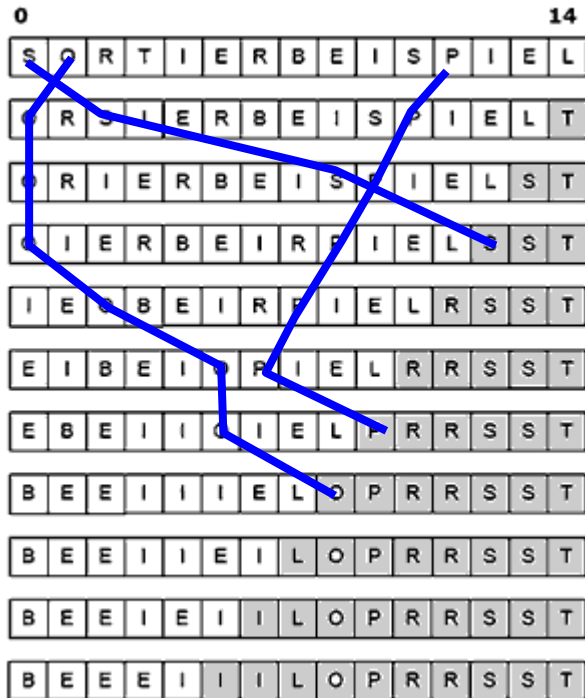
- Comparisons
 - Outer loop: n times
 - Inner-loop: i times
 - Thus, $O(n^2)$
- How many swaps?
 - (We move and don't swap, but both are in $O(1)$)
 - In worst-case, every comparison incurs a swap
 - Thus: $O(n^2)$
- We got worse?

Complexity (Best Case)

```
S: array_of_names;
n := |S|
for i = 2..n do
  j := i;
  key := S[j];
  while (S[j-1]>key) and (j>1) do
    S[j] := S[j-1];
    j := j-1;
  end while;
  S[j] := key;
end for;
```

- Assume the best case: S is **already sorted**
- Comparisons
 - Outer loop: n times
 - Inner-loop: 1 time
 - Thus, **$O(n)$**
- Swaps
 - None
- We might be better!

Bubble Sort



Source: HKI, Köln

- Go through array again and again
- Compare all **direct neighbors**
- Swap if in wrong order
- Repeat until a loop finishes without a single swaps
- Analysis: About as good/bad as the others (so far)
 - Worst case $O(n^2)$ comparisons and $O(n^2)$ swaps
 - Best case $O(n)$ comparisons and 0 moves / swaps

Summary

	Comparisons worst case	Comparisons best case	Additional space	Moves worst/best
Selection Sort	$O(n^2)$	$O(n^2)$	$O(1)$	$O(n)^*$
Insertion Sort	$O(n^2)$	$O(n)$	$O(1)$	$O(n^2) / O(n)$
Bubble Sort	$O(n^2)$	$O(n)$	$O(1)$	$O(n^2) / O(1)$

*: Key assignments

Summary

	Comparisons worst case	Comparisons best case	Additional space	Moves worst/best
Selection Sort	$O(n^2)$	$O(n^2)$	$O(1)$	$O(n)^*$
Insertion Sort	$O(n^2)$	$O(n)$	$O(1)$	$O(n^2) / O(n)$
Bubble Sort	$O(n^2)$	$O(n)$	$O(1)$	$O(n^2) / O(1)$
Merge Sort	$O(n \cdot \log(n))$	$O(n \cdot \log(n))$	$O(n)$	$O(n \cdot \log(n))$

Summary

	Comparisons worst case	Comparisons best case	Additional space	Moves worst/best
Selection Sort	$O(n^2)$	$O(n^2)$	$O(1)$	$O(n)^*$
Insertion Sort	$O(n^2)$	$O(n)$	$O(1)$	$O(n^2) / O(n)$
Bubble Sort	$O(n^2)$	$O(n)$	$O(1)$	$O(n^2) / O(1)$
Merge Sort	$O(n \cdot \log(n))$	$O(n \cdot \log(n))$	$O(n)$	$O(n \cdot \log(n))$
Magic Sort (?)	$O(n)$			$O(n)$

Content of this Lecture

- Sorting
- Simple Methods
- Lower Bound

Lower Bound

- We found three algorithms with WC-complexity $O(n^2)$
- Maybe there is **no better algorithm**?
- There are some in $O(n \cdot \log(n))$
- Maybe there are **even better** algorithms?

- Is there a **lower bound** on the number of comparisons?

Lemma

- Lemma
To sort a list of n distinct keys using only key comparisons, every algorithm needs $\Omega(n \cdot \log(n))$ comp's in worst case
- Implications
 - We cannot sort with less than $O(n \cdot \log(n))$ comparisons
 - Still, different algorithms with $O(n \cdot \log(n))$ may exhibit different real runtimes
 - We can be better, when **other operations** than comparisons are allowed – see radix sort

Proof Structure

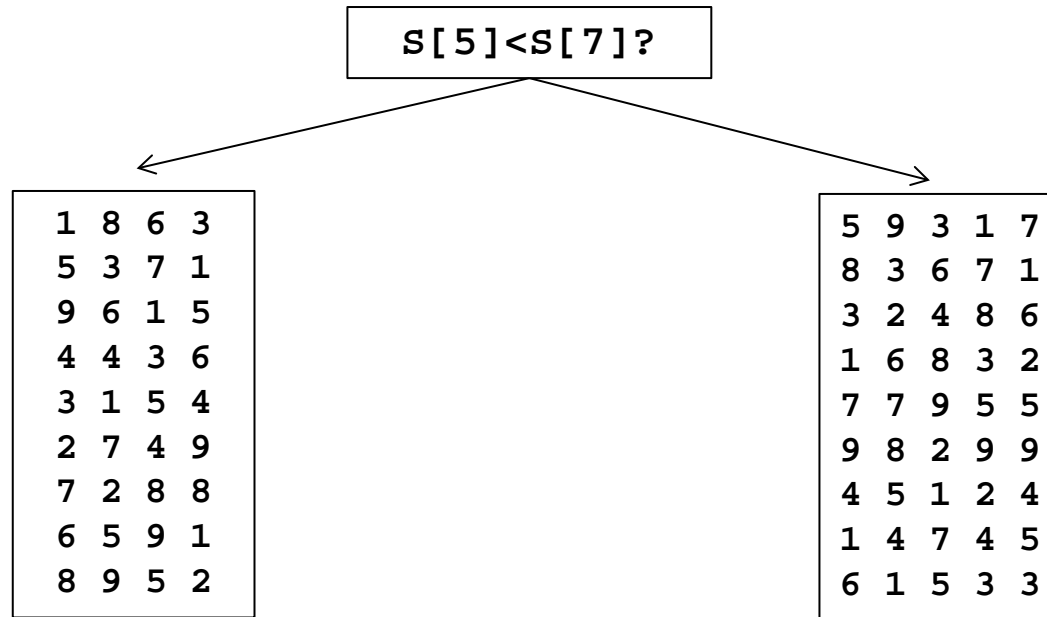
- We find the best way to find the **right permutation π**
- There are **$n!$ different** permutations
- Each could be the right one
 - And there is only one “right one”
- To find the right one, we may only compare two keys
- Every comparison we do splits the group of all permutations into **two disjoint partitions**
 - One with all permutations where the result of the test is TRUE
 - One with all permutations where the result of the test is FALSE
- How often do we need to compare at least such that **every partition eventually has size 1**
 - At least: In the best of all worlds

Decision Tree

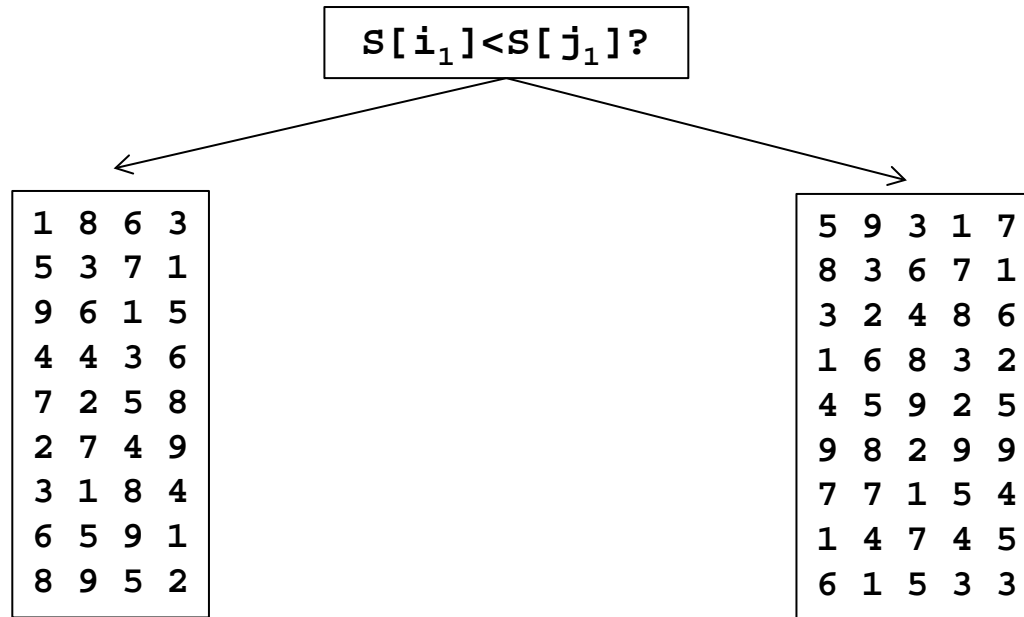
1	8	6	3	5	9	3	1	7
5	3	7	1	8	3	6	7	1
9	6	1	5	3	2	4	8	6
4	4	3	6	1	6	8	3	2
7	2	5	8	4	5	9	2	5
2	7	4	9	9	8	2	9	9
3	1	8	4	7	7	1	5	4
6	5	9	1	1	4	7	4	5
8	9	5	2	6	1	5	3	3

Some exemplary permutations
(columns) of an arbitrary list S
with $|S|=9$

General Case



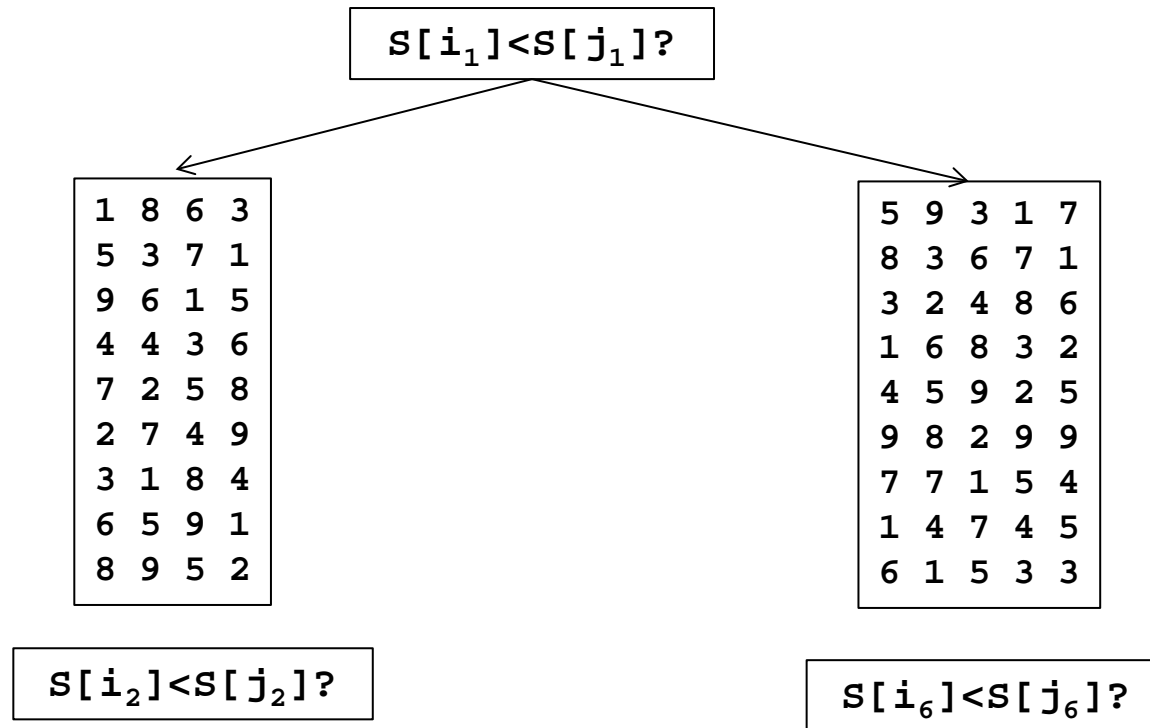
Decision Tree



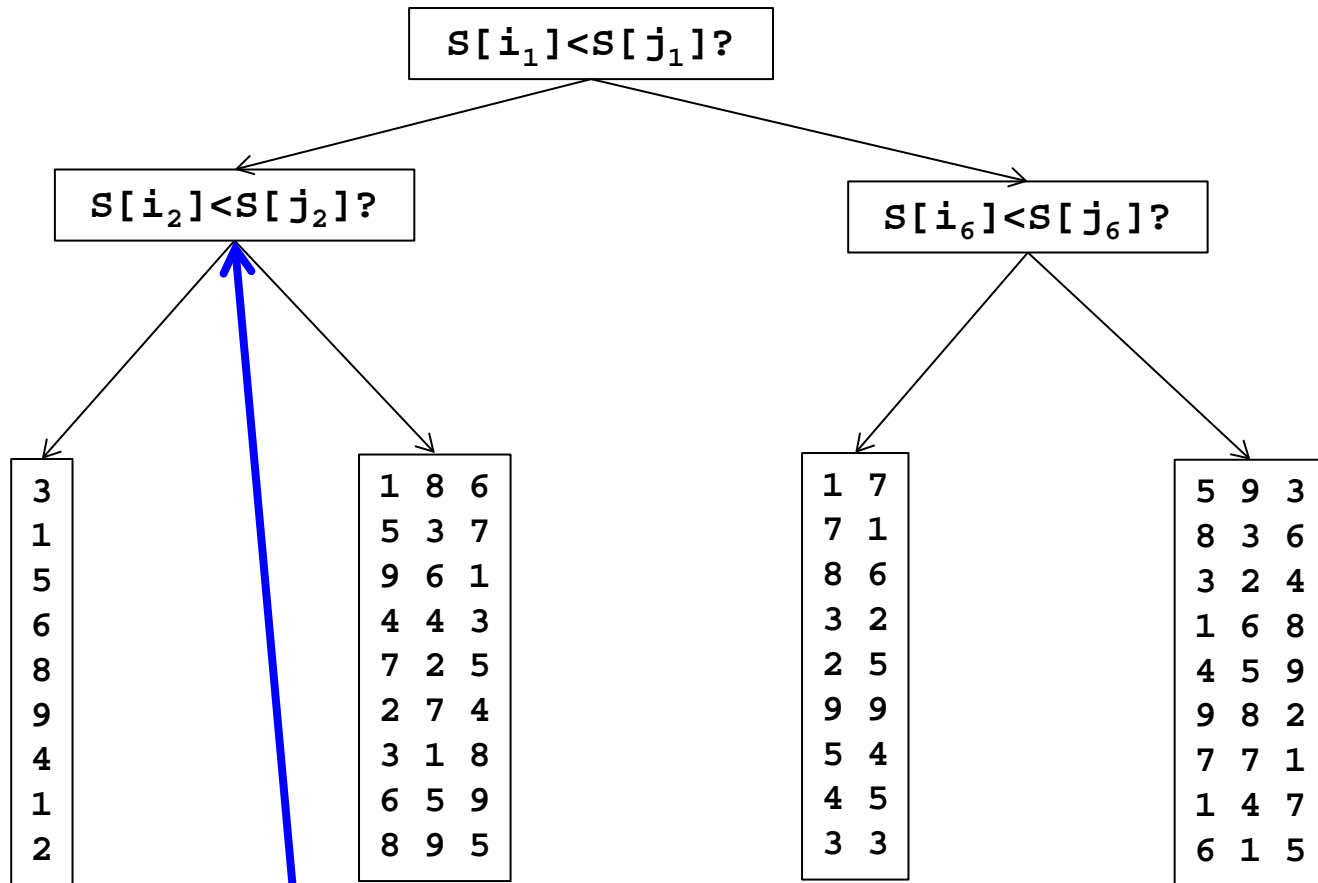
All permutations of S where
the value at position i_1 is
before the value at position j_1

All permutations of S where
the value at position i_1 is after
the value at position j_1

Decision Tree

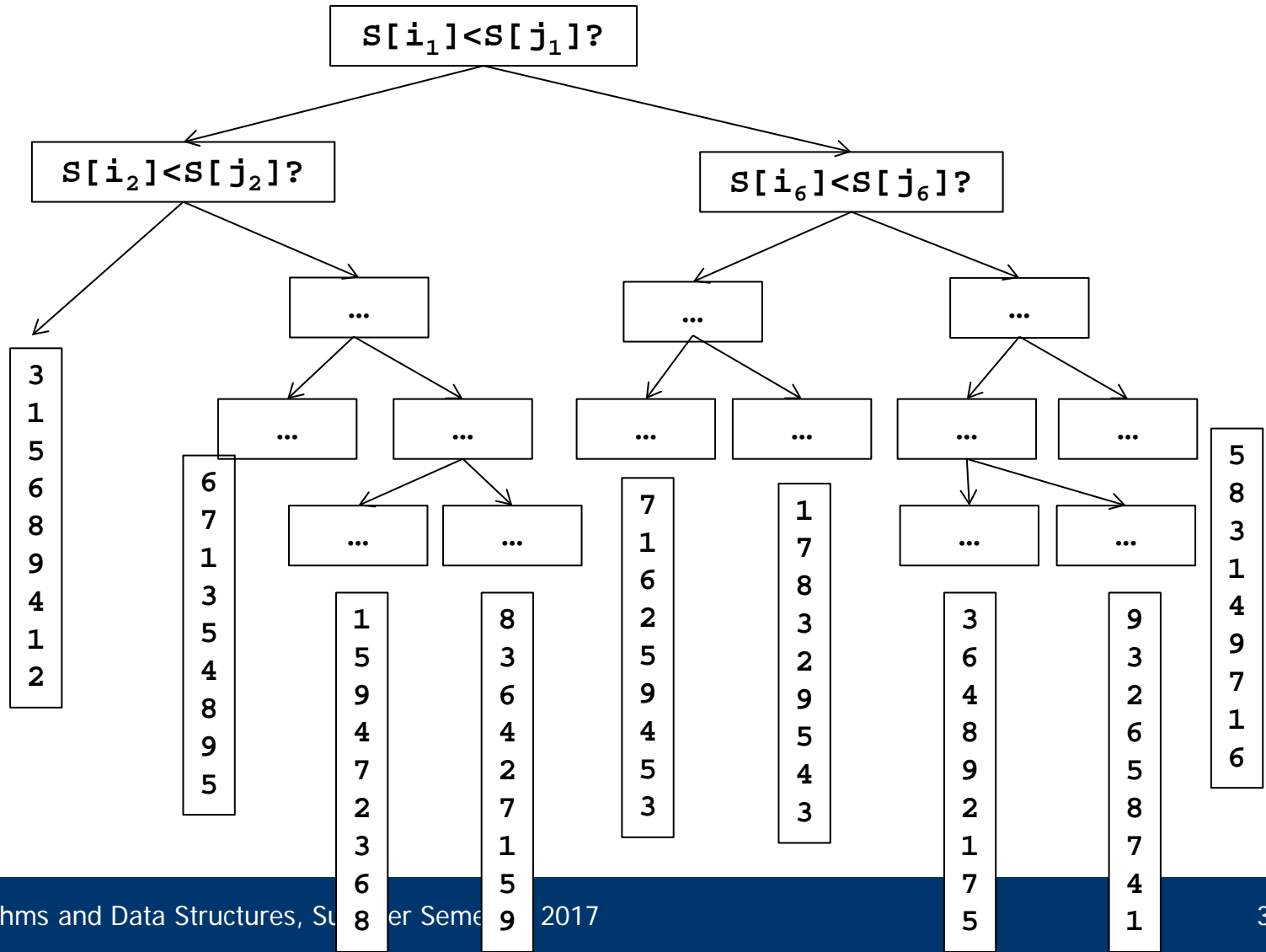


Decision Tree



Non-optimal choice of i_1, j_1

Full Decision Tree



Optimal Sequence of Comparisons

- We have no clue about which concrete series of comparisons is optimal for a given list
- But: Here we are looking for a lower bound: We may always assume to take **the best choice**
- Best choice: Creating all 1-partitions with **as few comparisons** as possible
- Thus, we want to know the **length of the longest path** through the **optimal (lowest) decision tree**
 - Even in the best of all worlds we may need to make this number of comparisons to find the correct permutation
- The optimal tree is the one with the **shortest longest path**

Shortest Longest Path

- Definition

*The **height of a binary tree** is the length of its longest path.*

- Lemma

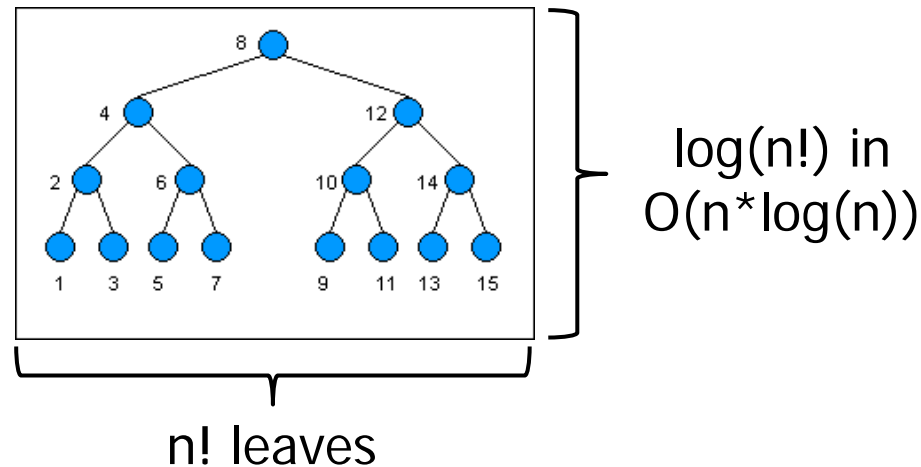
*A binary tree with k leaves has **at least height $\log(k)$.***

- Proof

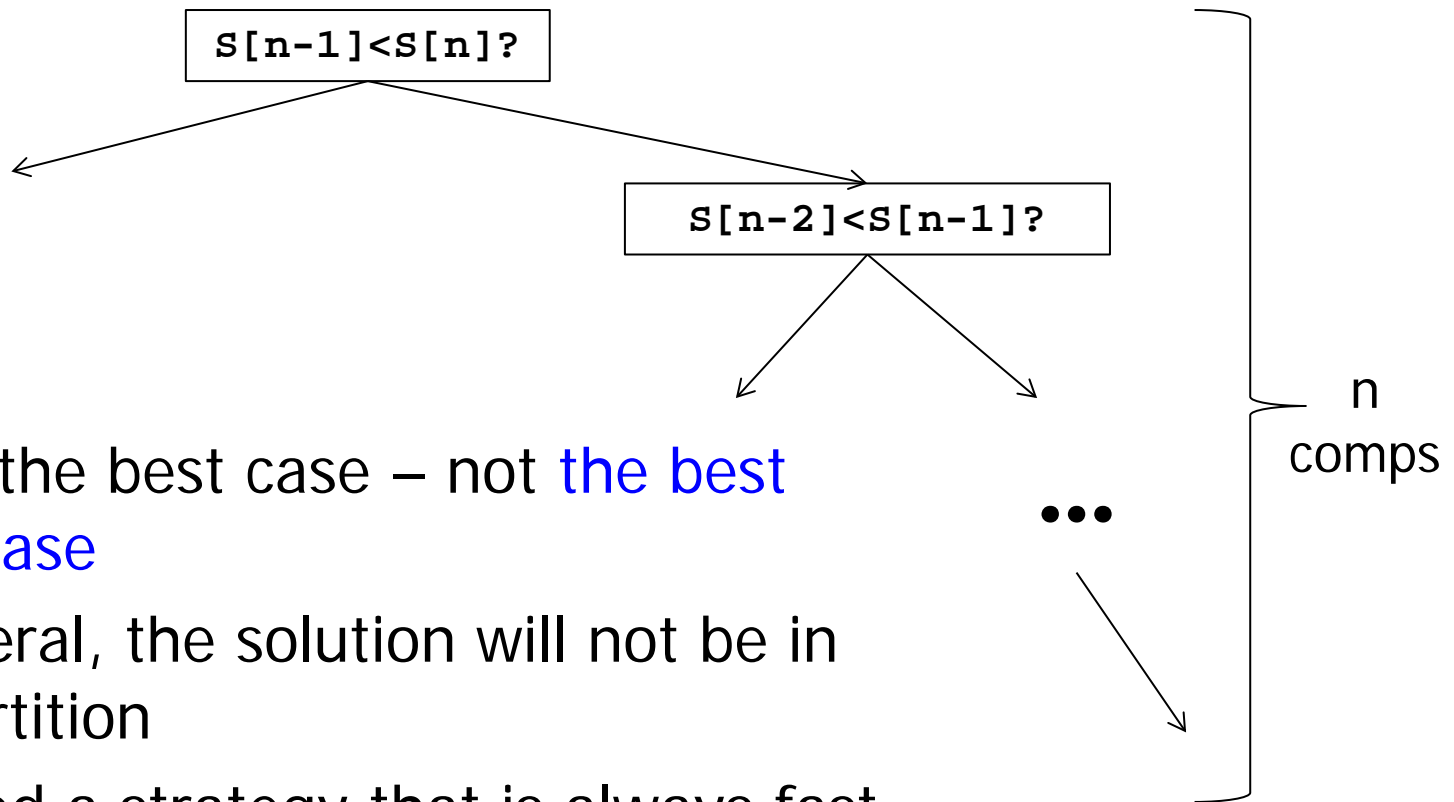
- Every **inner node has at most two children**
- To cover as many leaves as possible in the level **above the leaves**, we need $\text{ceil}(k/2)$ nodes
- In the second-last level, we need $\text{ceil}(k/2/2)$ nodes
- Etc.
- After $\log(k)$ levels, only one node remains (root)
- qed.

Putting it all together

- Our decision tree has $n!$ leaves
- The height of a binary tree with $n!$ leaves is **at least $\log(n!)$**
- Thus, the **longest path** in the optimal tree has at least $\log(n!)$ comparisons
- Since $n! \geq (n/2)^{n/2}$: $\log(n!) \geq \log((n/2)^{n/2}) = n/2 * \log(n/2)$
- This gives the overall **lower bound $\Omega(n * \log(n))$**
- qed.



Stop: Why not test in $O(n)$?



- This is the best case – not **the best worst case**
- In general, the solution will not be in this partition
- We need a strategy that is always fast, not “faster” in some cases

Exemplary Exam Questions

- Give best case and worst case instances for the following algorithms: insertion sort, bubble sort. Explain your examples
- Proof that bubble sort is in $O(n^2)$ and $\Omega(n^2)$ worst case (comparisons)
- Imagine a list S consisting of k sorted subarrays of arbitrary size (example for $k=4$: $\langle 1,6,7,8,2,5,1,5,7,9,3,5 \rangle$). Find an algorithm for sorting S which runs in $O(n \cdot k)$