

# **Advanced Algorithmic Techniques (COMP523)**

Recursion and Divide and Conquer Techniques #2

# Recap and plan

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- **Last lecture:**
  - Asymptotic Complexity.
  - Searching in logarithmic time.
  - Finding majority in an array.

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- **Last lecture:**
  - Asymptotic Complexity.
  - Searching in logarithmic time.
  - Finding majority in an array.
- **This lecture:**
  - Sorting with the **MergeSort** algorithm.
  - Sorting with the **QuickSort** algorithm.
  - The limitations of comparison-based sorting.

# Sorting with Mergesort

# Merging two sorted arrays

- Given two sorted arrays  $\mathbf{A}[1, \dots, n]$  and  $\mathbf{B}[1, \dots, m]$ , produce a sorted array  $\mathbf{C}[1, \dots, n+m]$  containing all the elements of  $\mathbf{A}$  and  $\mathbf{B}$ .

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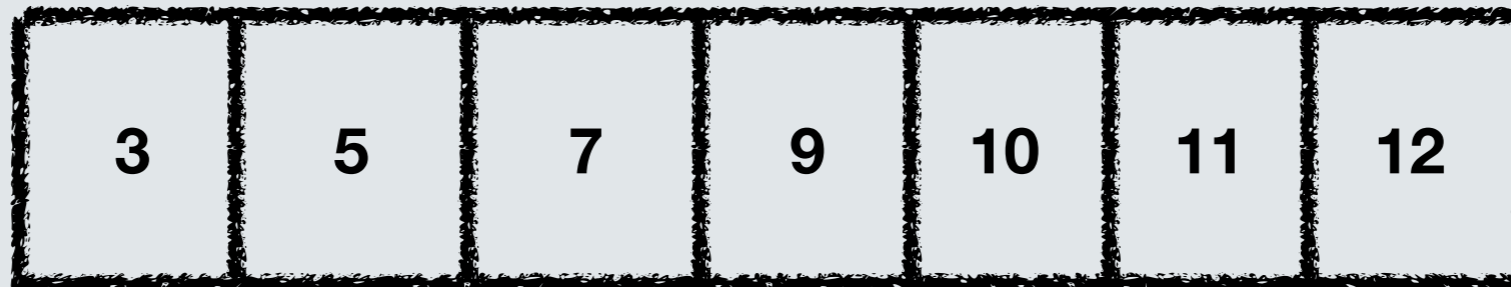
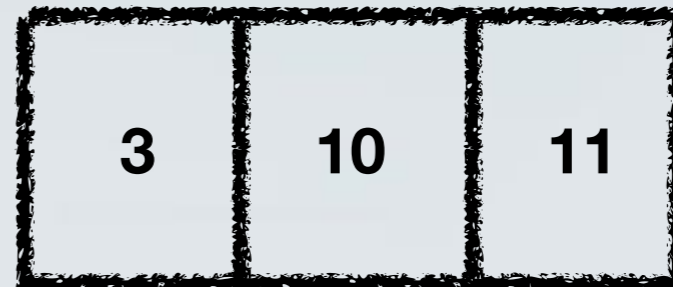
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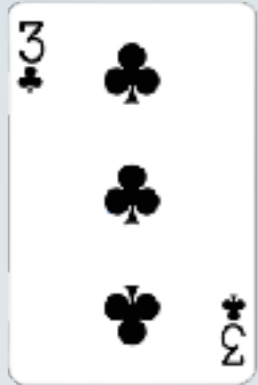
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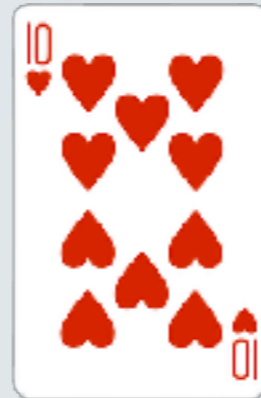
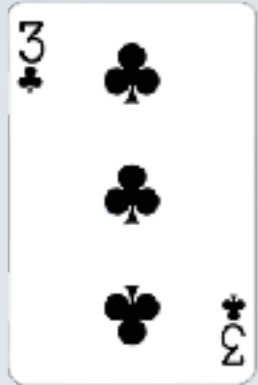
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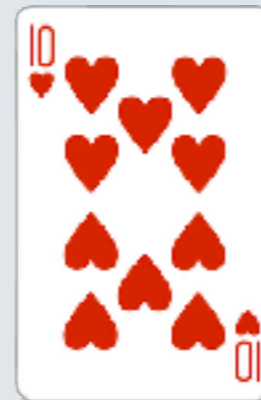
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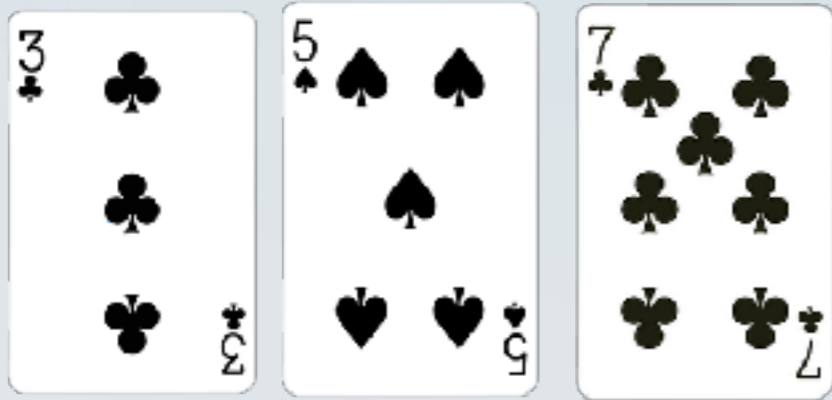


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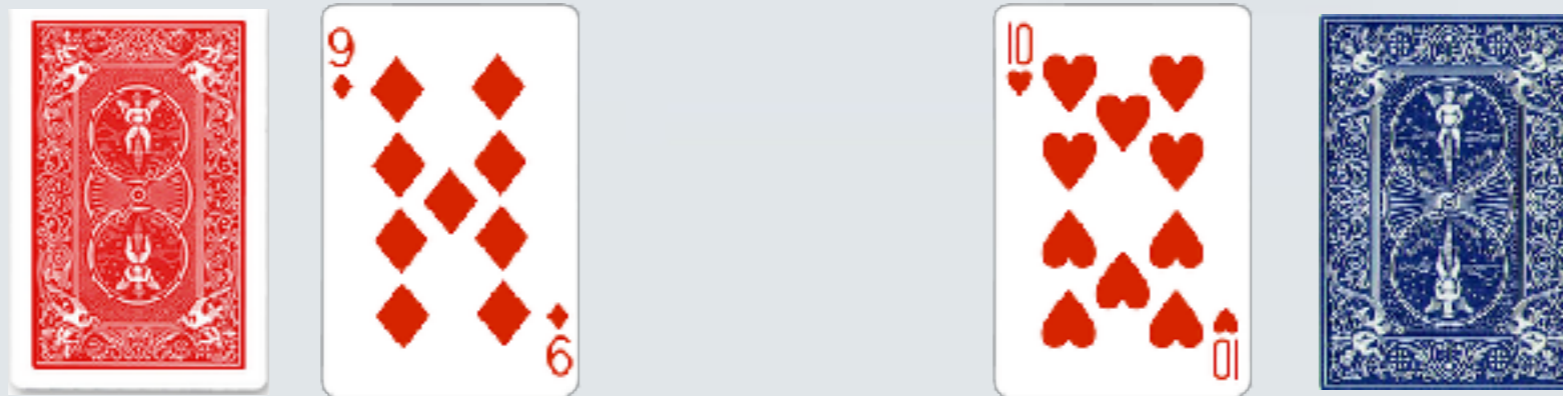




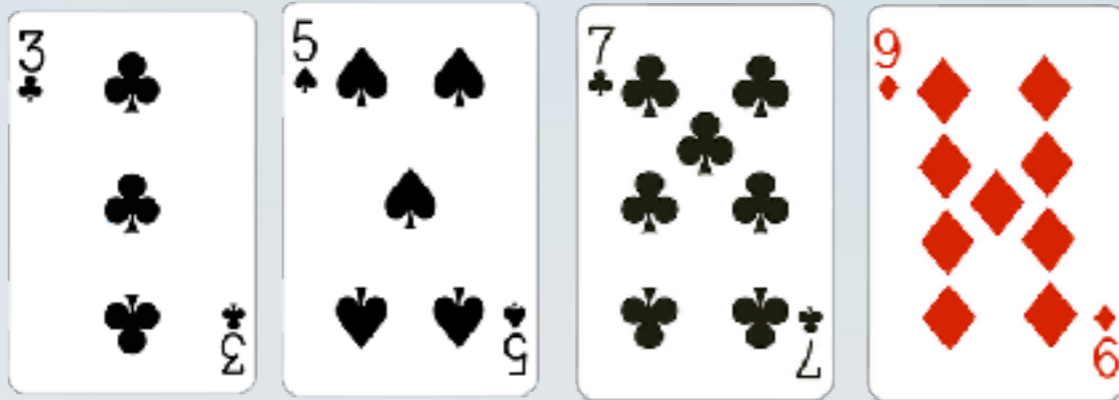
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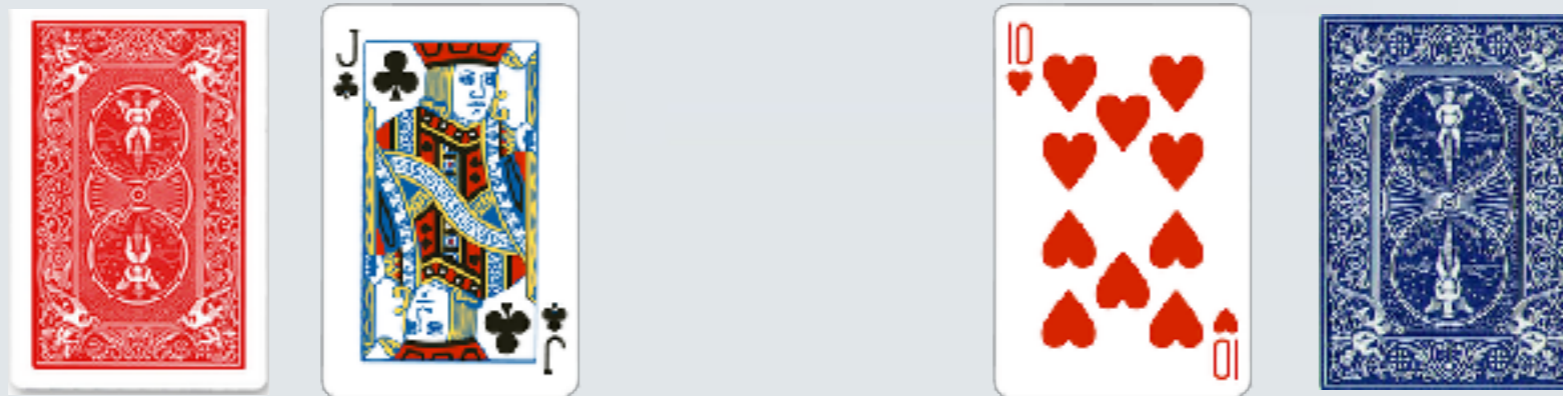
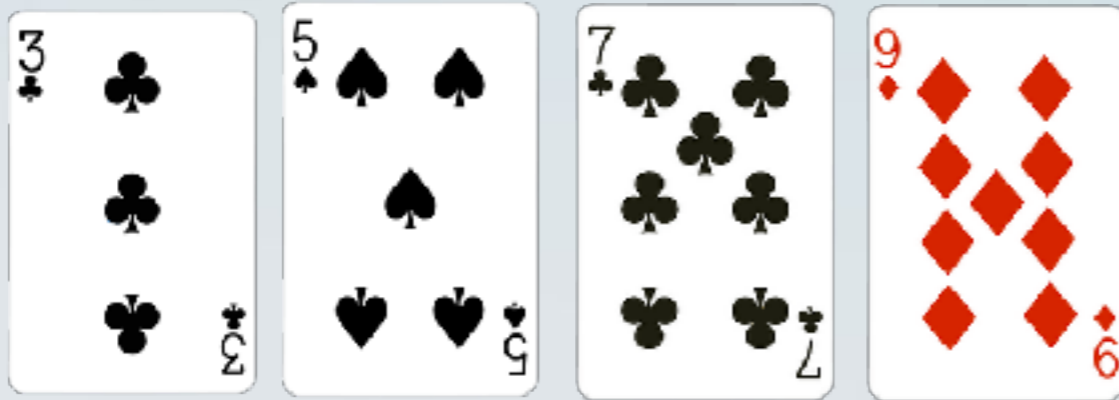
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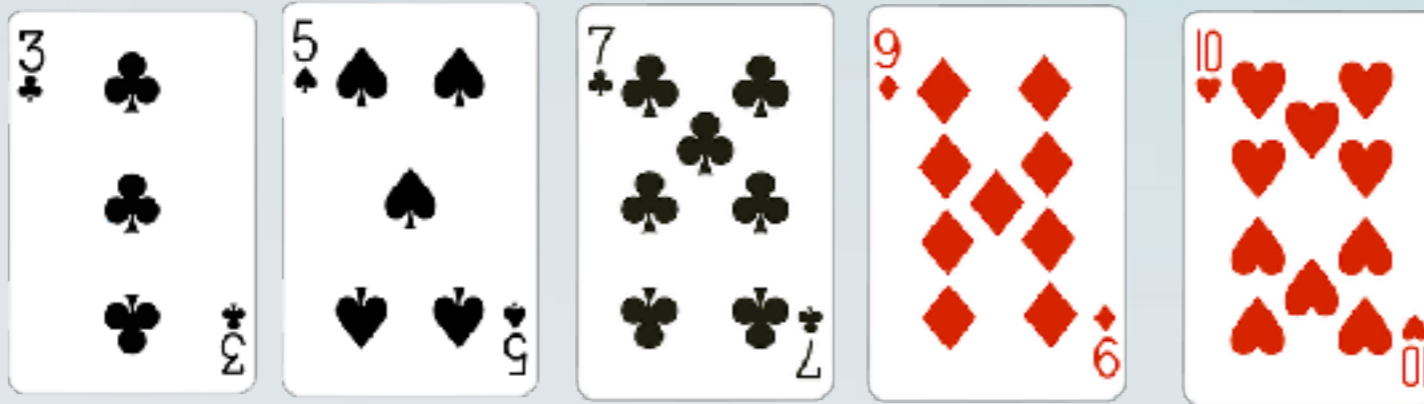
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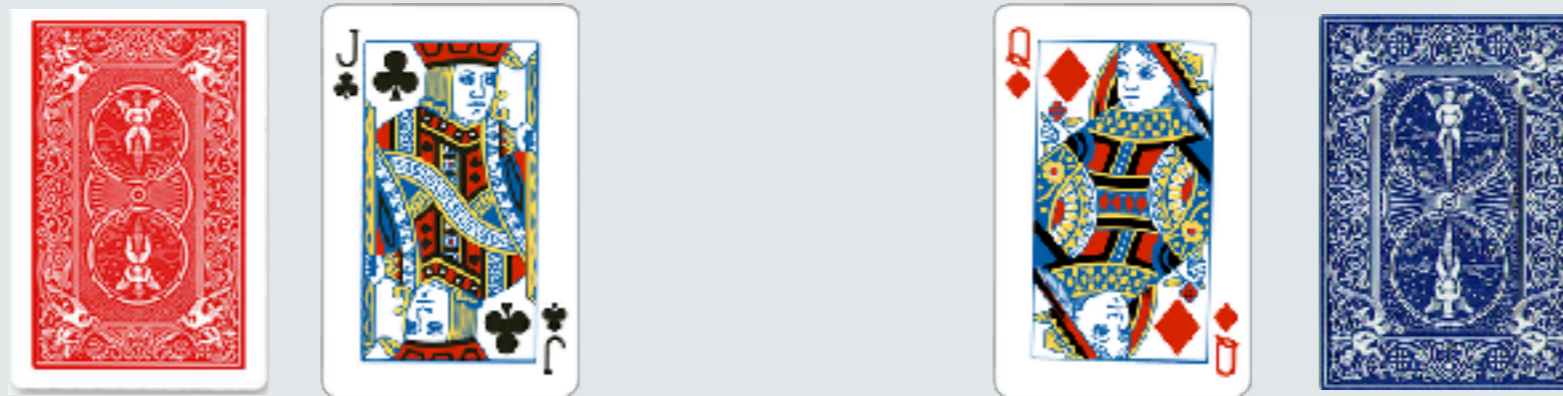
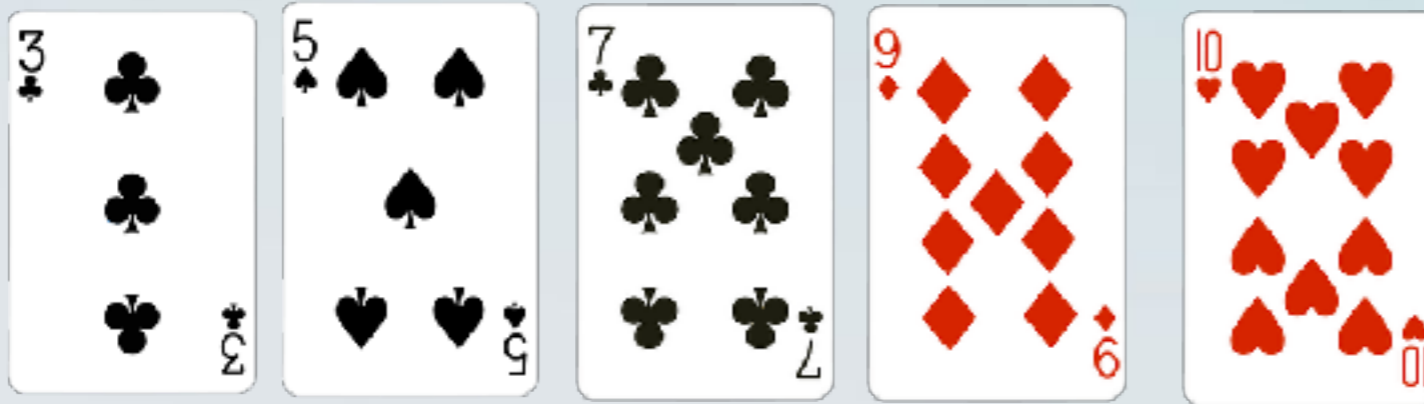
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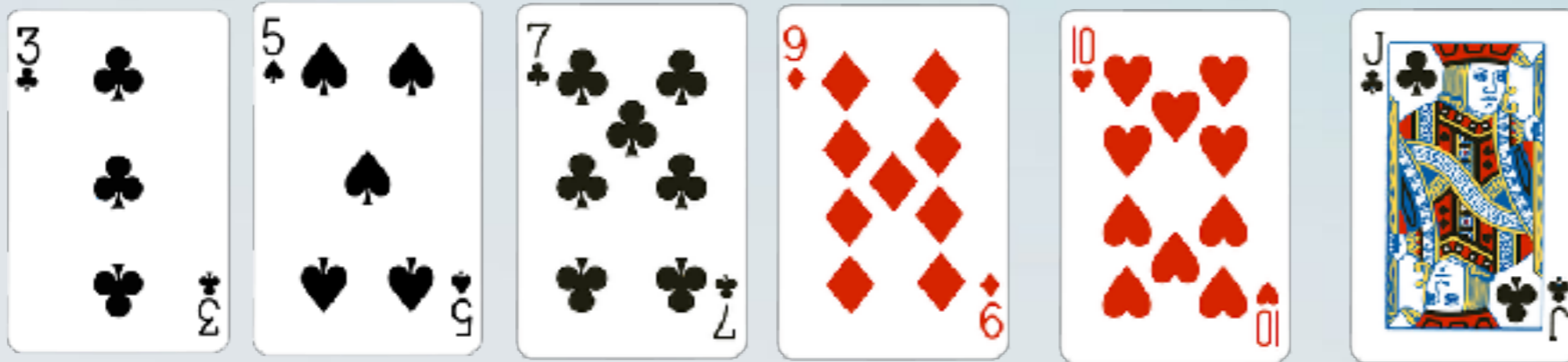
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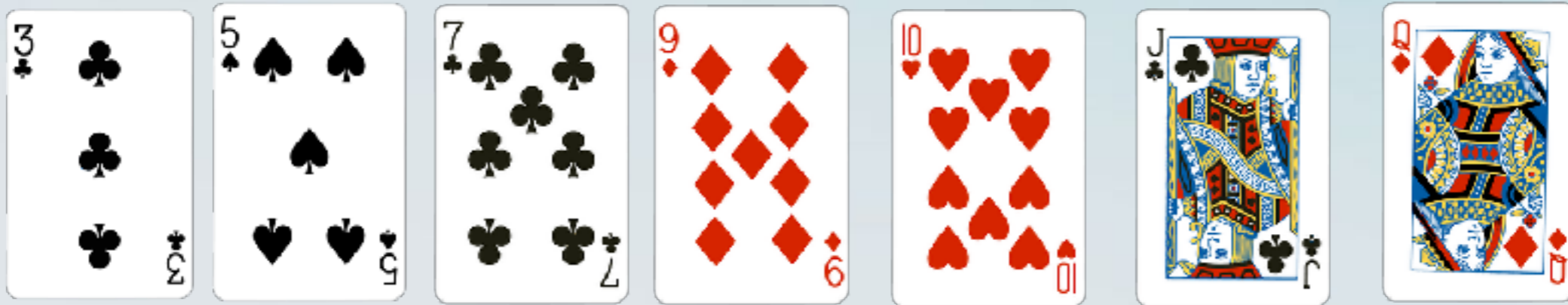
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# Procedure Merge

Procedure **Merge**(**A**, **B**)

*/\* Recall that  $|\mathbf{A}| = n$  and  $|\mathbf{B}| = m$  \*/*

Initialise array **C** of size  $n+m$

$i=1, j=1$

For  $k=1, \dots, m+n-1$

    If  $\mathbf{A}[i] \leq \mathbf{B}[j]$

$\mathbf{C}[k] = \mathbf{A}[i]$

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**$O(m+n)$**

# The Mergesort algorithm

- Divide and conquer algorithm.
- Split the array  $\mathbf{A}[1, \dots, n]$  to two subarrays,  $\mathbf{A}[1, \dots, n/2]$  and  $\mathbf{A}[n/2+1, \dots, n]$
- Sort each subarray using Mergesort.
  - Stop the recursion when the subarray contains only one element.
- Merge the sorted subarrays  $\mathbf{A}[1, \dots, n/2]$  and  $\mathbf{A}[n/2+1, \dots, n]$  using the Merge procedure.



# Mergesort pseudocode

Algorithm **Mergesort**( $\mathbf{A}[i, \dots, j]$ )

If  $i=j$ , return  $i$

$q=(i+j)/2$

$\mathbf{A}_{\text{left}}=\mathbf{Mergesort}(\mathbf{A}[i, \dots, q])$

$\mathbf{A}_{\text{right}}=\mathbf{Mergesort}(\mathbf{A}[q+1, \dots, n])$

return **Merge**(  $\mathbf{A}_{\text{left}}$  ,  $\mathbf{A}_{\text{right}}$  )

# Mergesort pseudocode

Algorithm **Mergesort**(**A**[*i*, ..., *j*])

If  $i=j$ , return  $i$

Initial call: **Mergesort**(**A**[*i*, ..., *n*])

$q=(i+j)/2$

**A**<sub>left</sub>=**Mergesort**(**A**[*i*, ..., *q*])

**A**<sub>right</sub>=**Mergesort**(**A**[*q*+1, ..., *n*])

return **Merge**( **A**<sub>left</sub> , **A**<sub>right</sub> )

# Mergesort example

6	4	8	9	2	1	3
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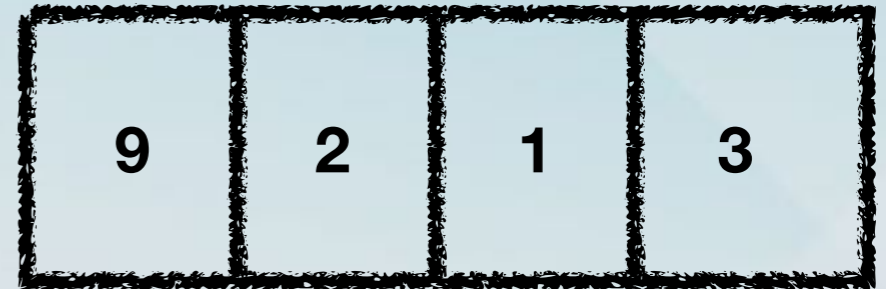
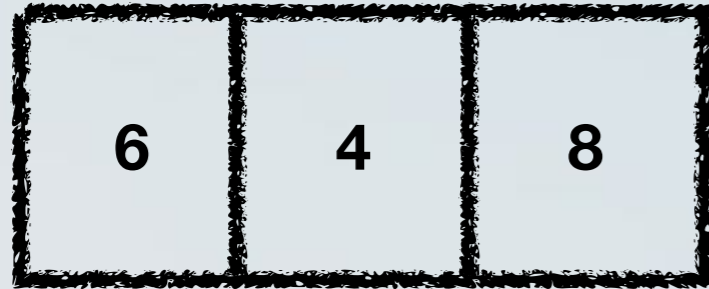
# Mergesort example

divide

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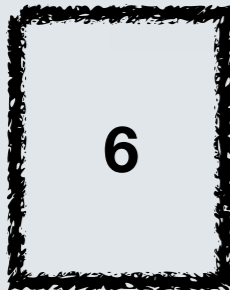
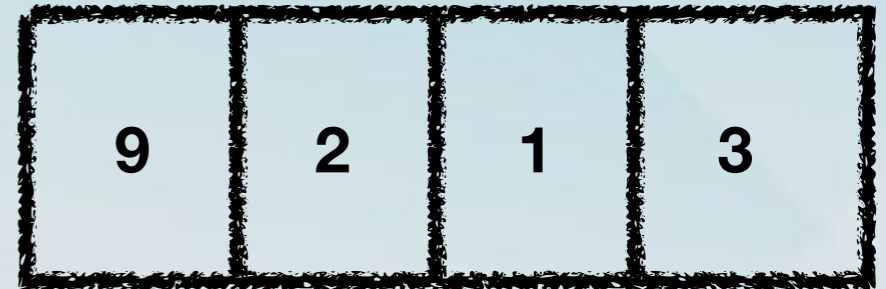
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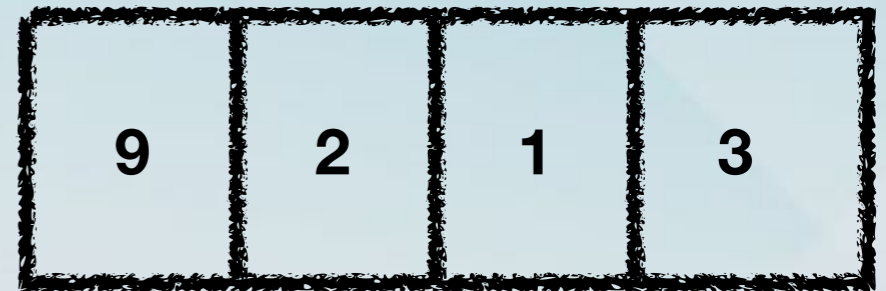
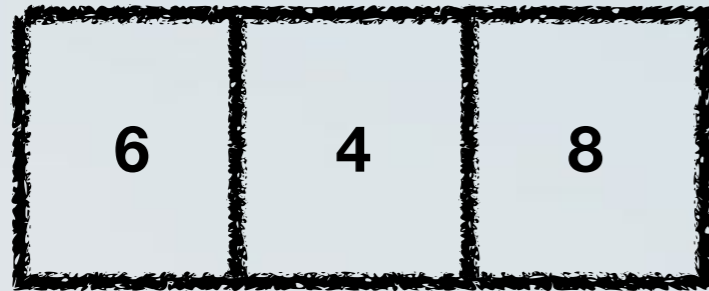
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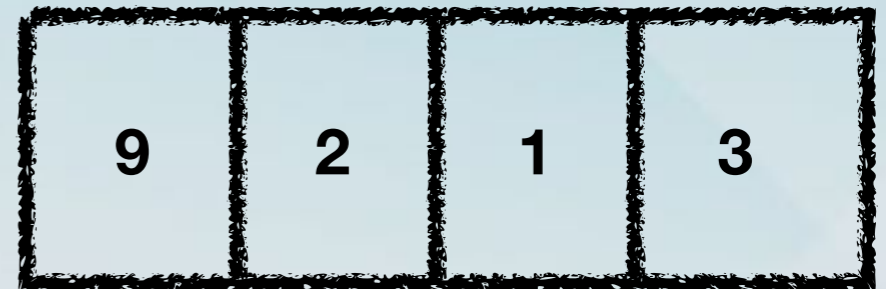
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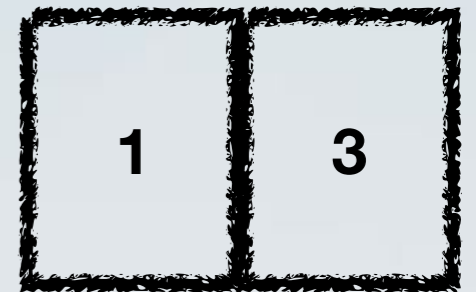
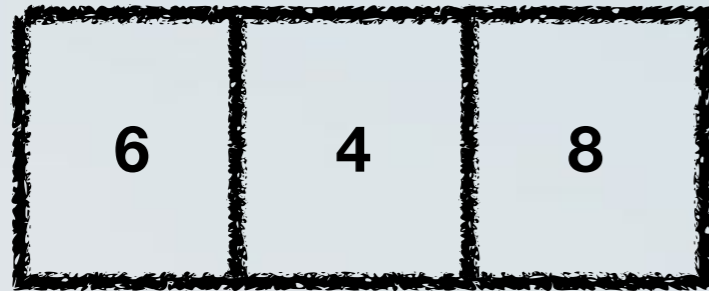
divide





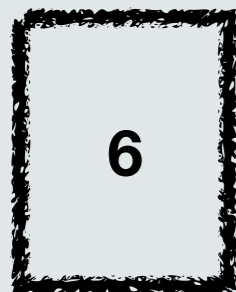
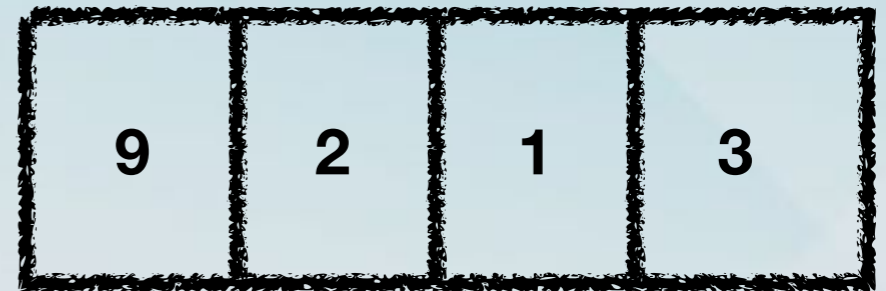
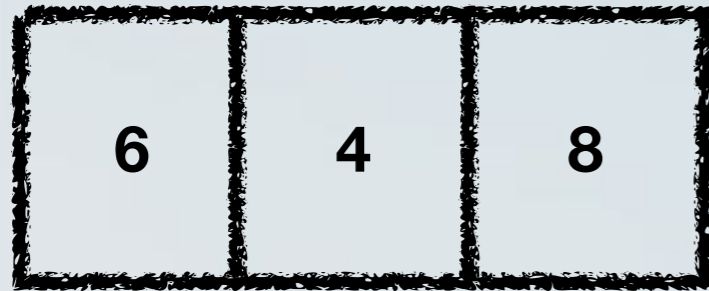
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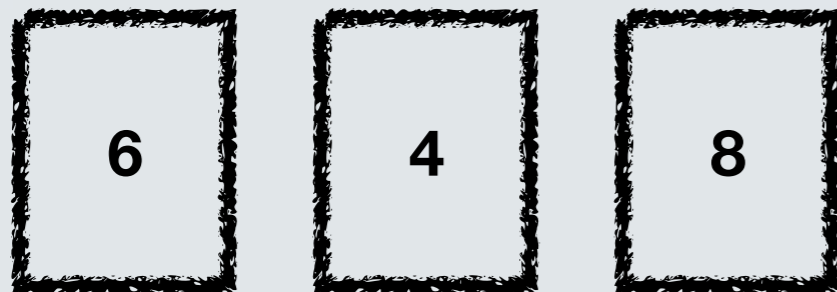
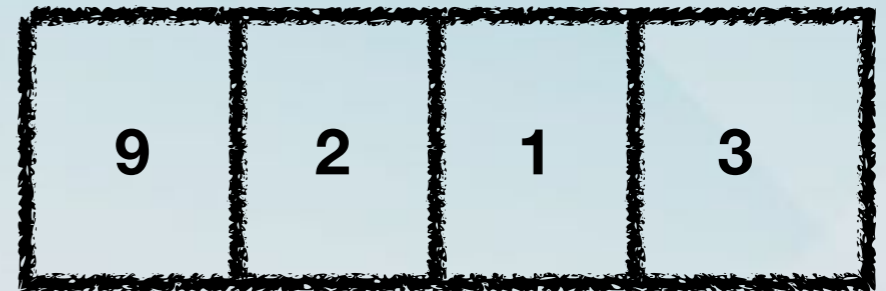
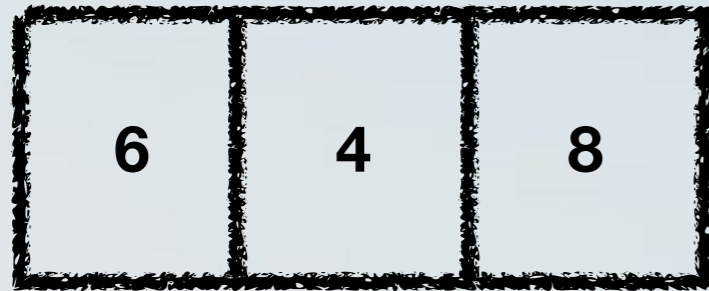
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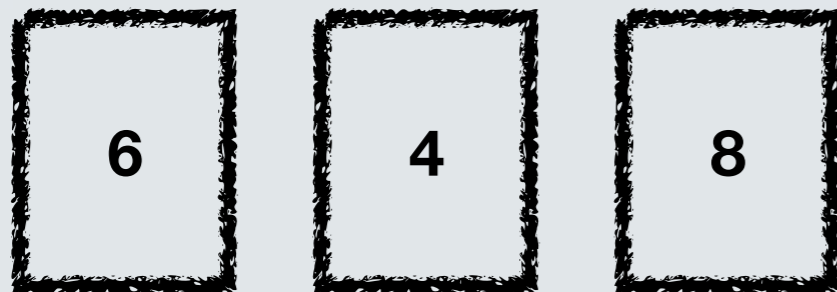
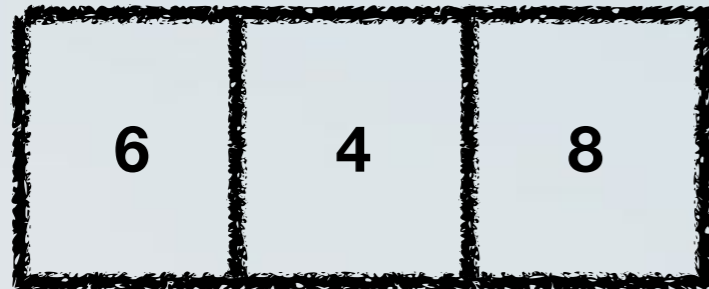
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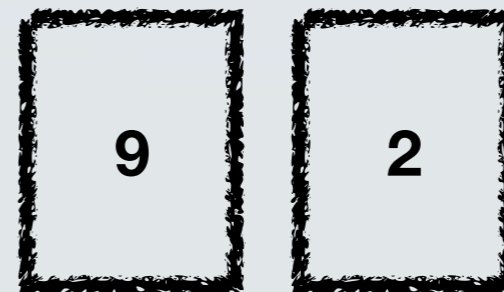
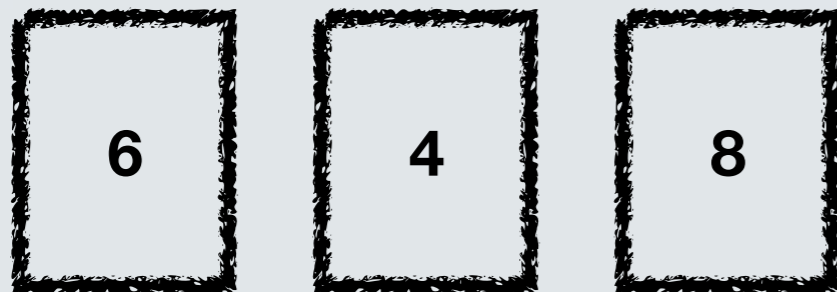
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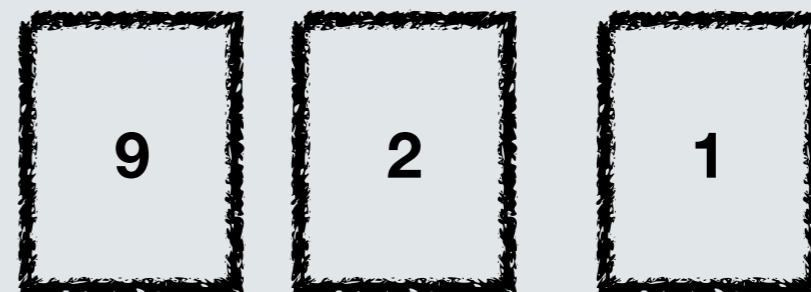
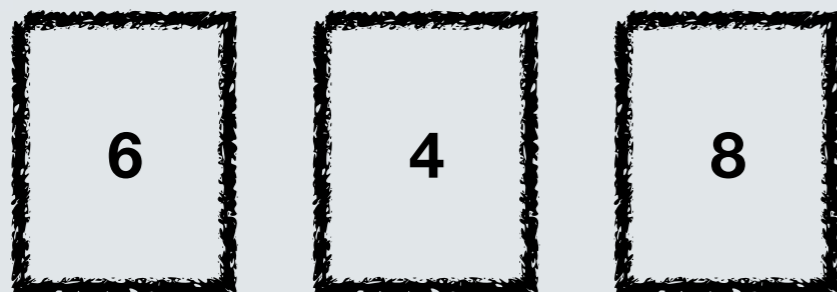
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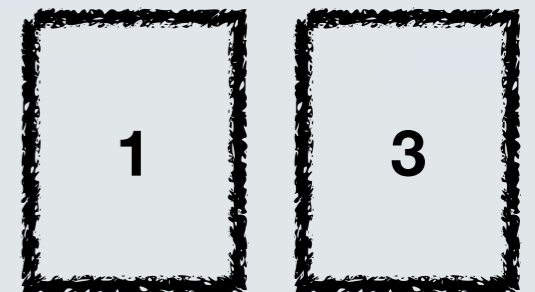
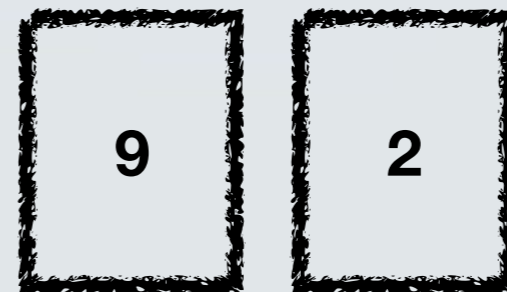
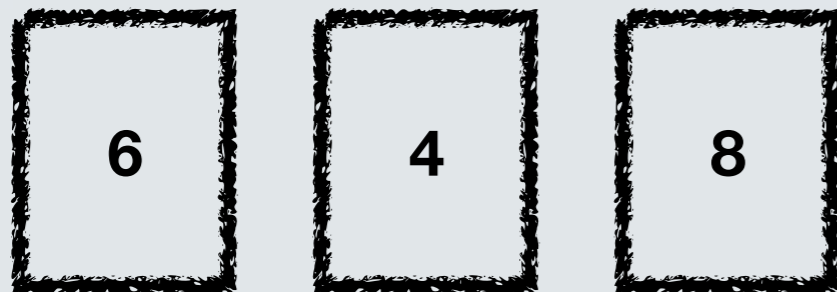
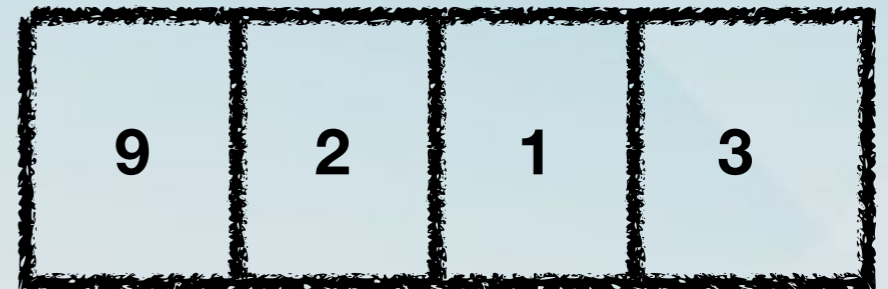
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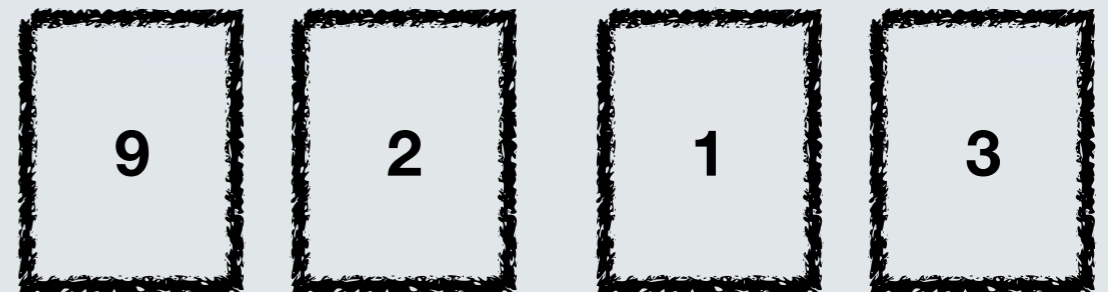
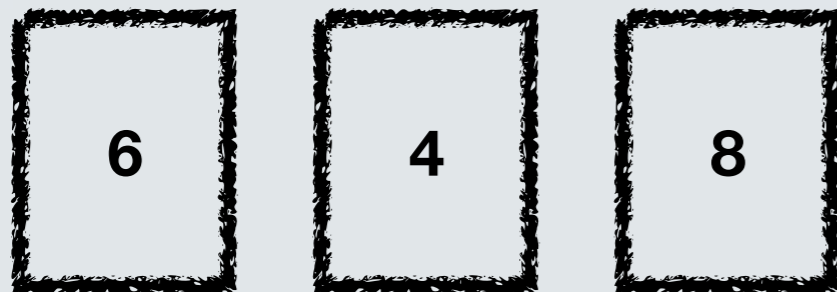
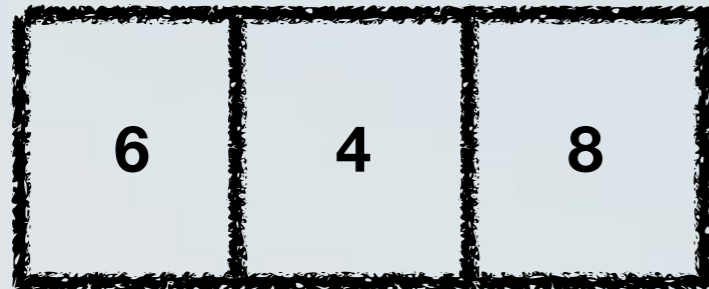
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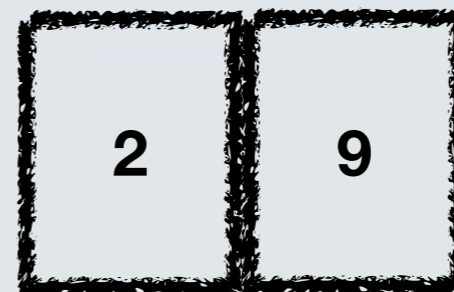
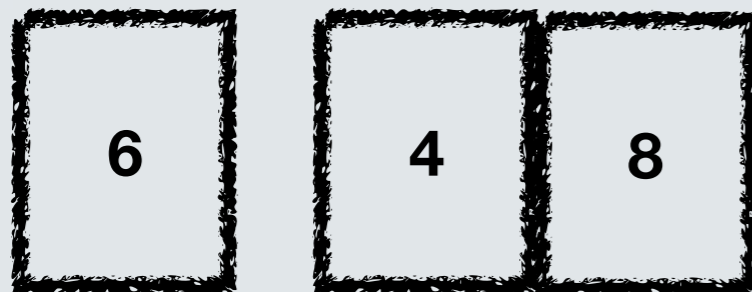
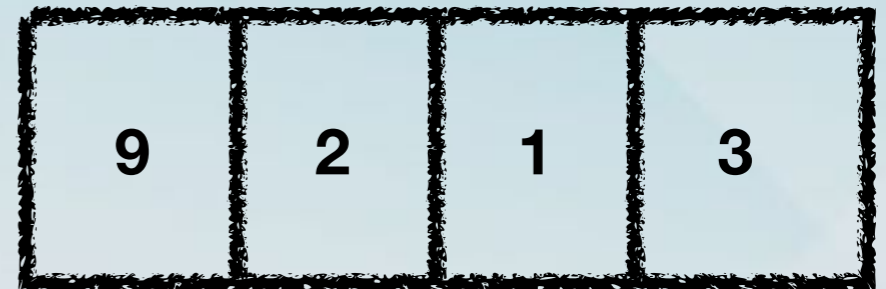
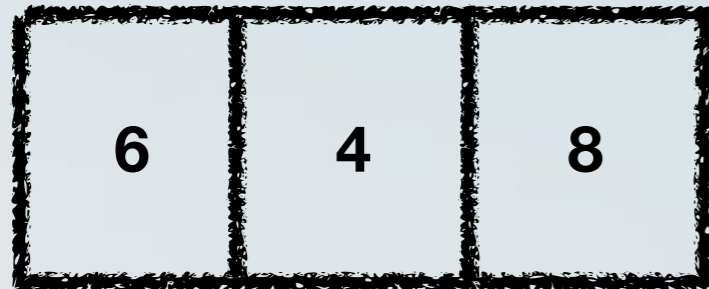
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divide merge



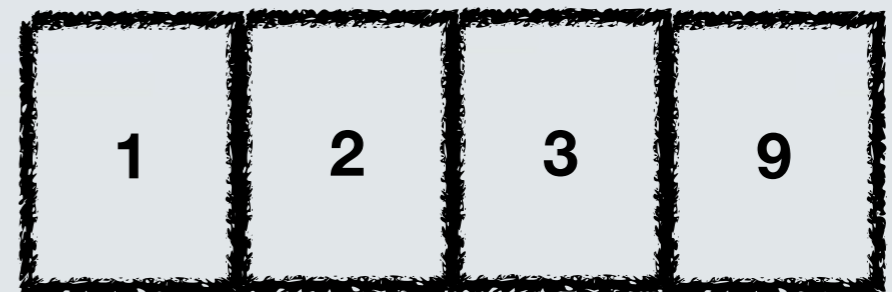
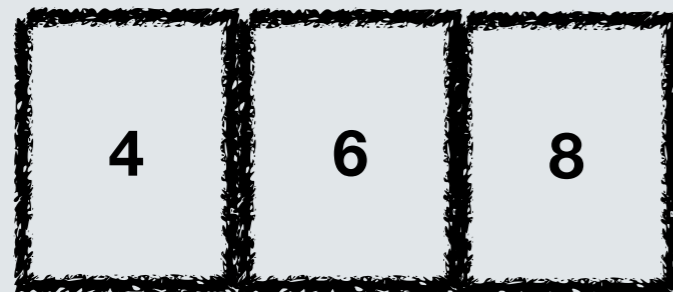
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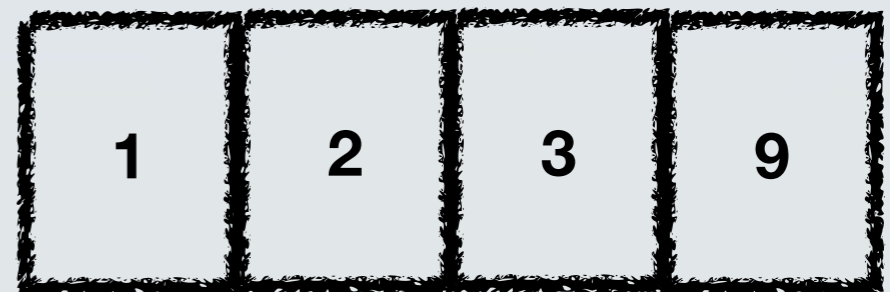
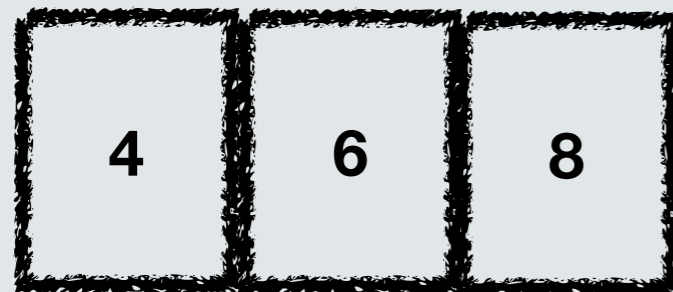
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# Running time of Mergesort

- We could guess the running time and prove it using induction, as we saw in the previous lecture.
- Instead, we will try to “figure out” what the running time should be.
- We will use the method of **recursion trees**.
- The running time is generally

$$T(n) = 2T(n/2) + f(n)$$

# Running time of Mergesort

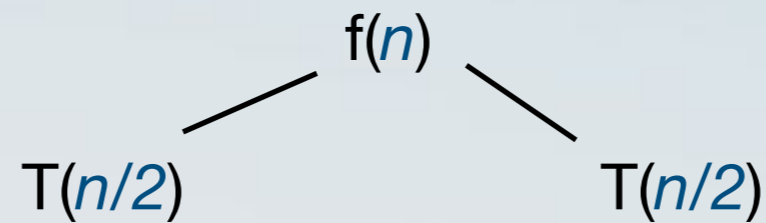
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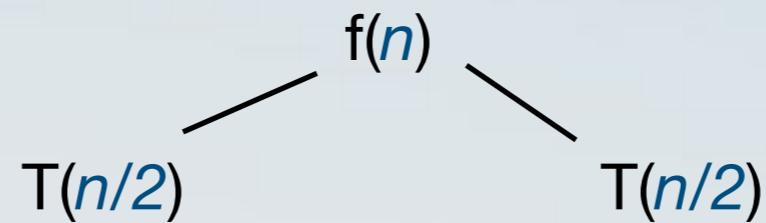




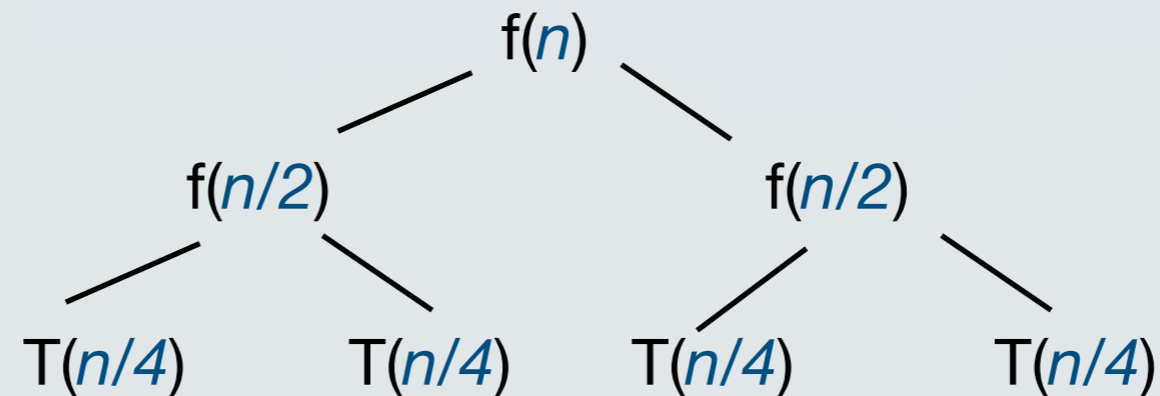
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**Second iteration:** Price of  $f(n/2)$  for each subproblem, plus the cost of two subproblems of size  $n/4$



# Running time of Mergesort

- In total, there will be  $\log n + 1$  levels (input halved every time).
  - Level 0 has cost  $C_0(n) = f(n)$
  - Level 1 has cost  $C_1(n) = 2f(n/2)$
  - Level 2 has cost  $C_2(n) = 4f(n/4)$
  - Level  $j$  has cost  $C_j(n) = 2^j f(n/2^j)$
  - The last level has cost  $f(n)$

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$$T(n) = \sum_{j=1}^{\log n - 1} C_j(n) + f(n)$$

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- The overall running time is  **$O(n \log n)$** .

# Sorting with Quicksort

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- The two parts are joined, but this is trivial.



# The Partition procedure

Procedure **Partition**( $A[i, \dots, j]$ )

Choose a **pivot element**  $x$  of  $A$

$k = i - 1$

For  $h = i$  to  $j - 1$  do

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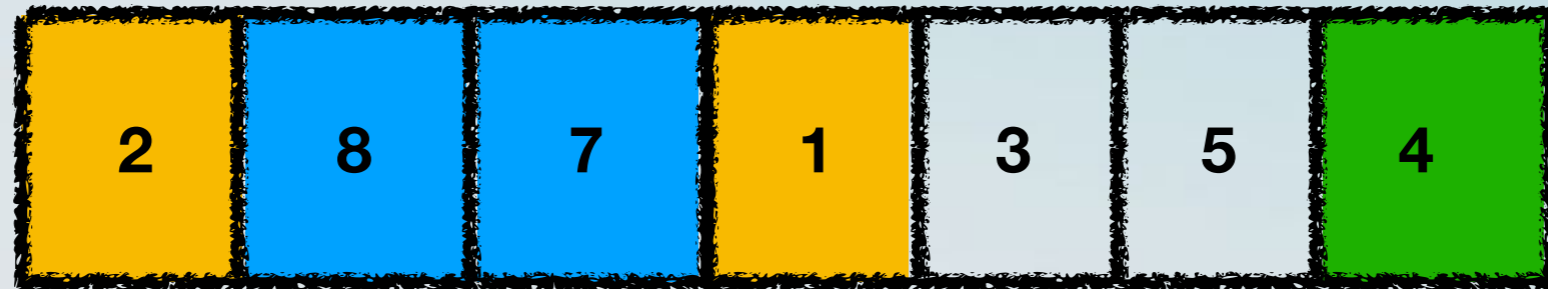


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Sort this using  
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Algorithm **Quicksort**( $A[i, \dots, j]$ )

$y =$  **Partition**( $A[i, \dots, j]$ )

**Quicksort**( $A[i, \dots, y-1]$ )

**Quicksort**( $A[y+1, \dots, j]$ )

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***What is the worst possible running time?***

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# Lower bound for (comparison-based) sorting

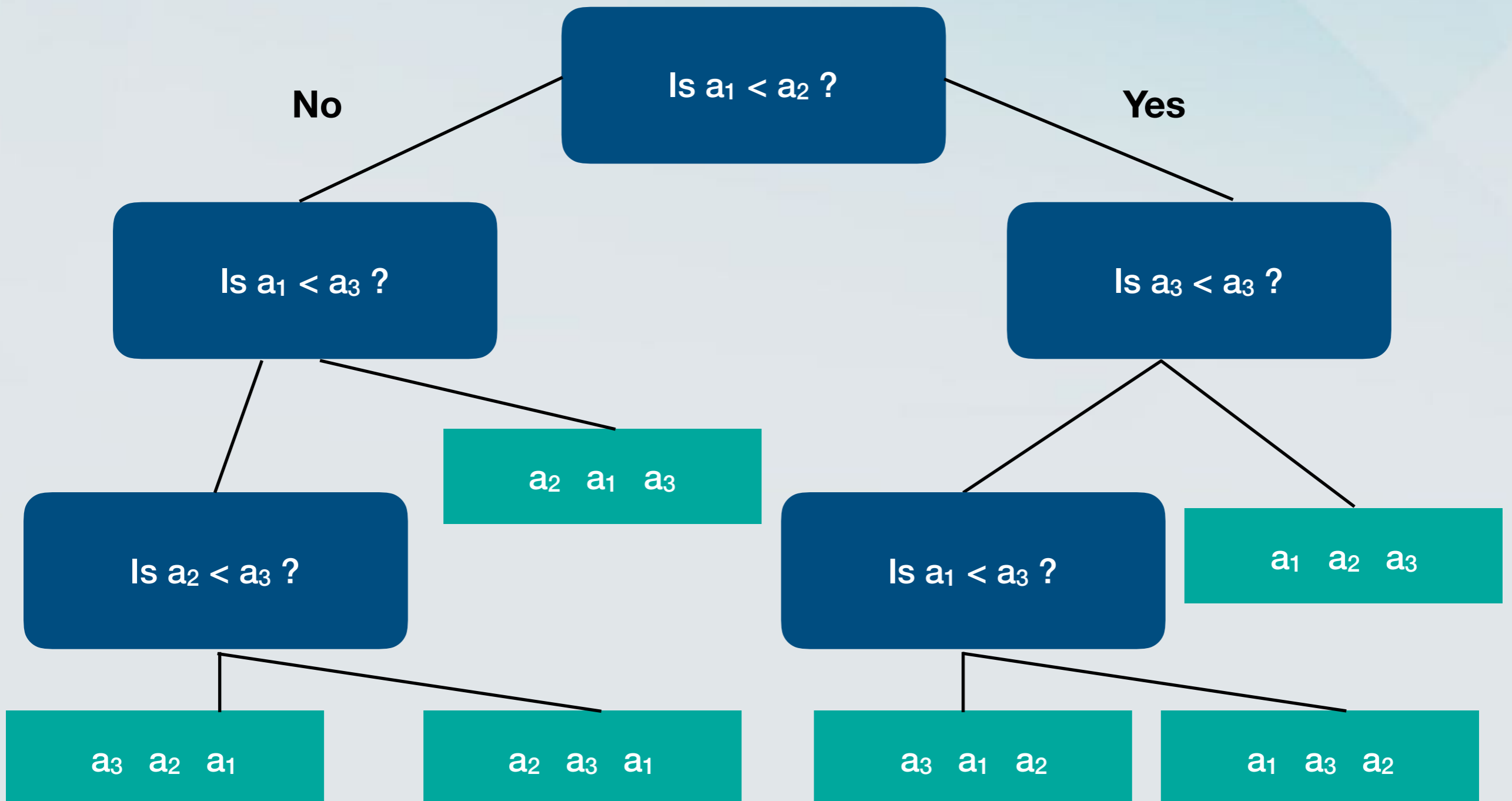
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- In other words, we will prove that for any such algorithm, the running time is  $\Omega(n \log n)$ .

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  - Every possible permutation can appear as a leaf, since every possible permutation is a valid output.

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$$\begin{aligned}\log(n!) &= \log(1 * 2 * \dots * n) = \log(1) + \log(2) + \dots + \log(n) \\ &\geq \log(n/2) + \dots + \log(n) \text{ (half)} \\ &\geq \log(n/2) + \dots + \log(n/2) \\ &= (n/2) * \log(n/2)\end{aligned}$$

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  - We try to design algorithms which are as good as possible and when we feel that we can not improve more, we try to prove the **matching** lower bound.

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- Stay tuned!