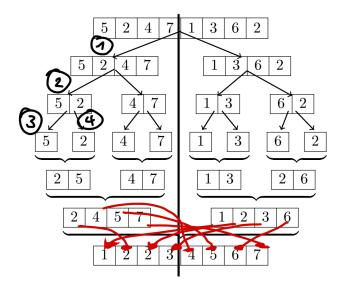
# Divide and conquer

Divide and conquer has 3 central steps

- Divide into subproblems
- Concauer subproblems with recursive solution
- Combine solution of subproblems into solution for the original problem

#### ## Merge sort

- Divide: divide the sequence into two n/2-element sequences
- Conquer: sort the two sequences recursively using merge sort
- Combine: merge the two sorted sequences to produce the solution



```
Algorithm MergeSort(1, h)
{
    if(1<h)
    {
        mid = (1+h)/2;
        MergeSort(1, mid)
        MergeSort(mid + 1, h)
        Merge(1, mid, h)
    }
}</pre>
```

Time complexity for Merge Sort is  $\Theta(n \log n)$ . The logic behind this is determined from the recursion calls. With 8 elements split into "groups" of 2 elements each, we have 3 levels, where a merge happens  $(2^3 = 8)$ .

## Reccurences

The running times of algorithms with recursive calls can be described using recurrences. There exist 4 basic ways how we can get to the reuccurence formula:

- Repeated (backward) substitution: Expand the recurrence by substitution and then notice the pattern
- Substitution method: Guess a bound and then use induction to prove that the guess is correct
- Recursion trees: Convert a recurrence in a tree whose nodes represent the costs
- Master method: Templates for different classes of recurrences

### Repeated substitution

The pattern we see here is  $2^iT(\frac{n}{2})+2in+3\sum_{i=1}^{j=0}2^j$  - to clarify, the i and j stand for the number of substituions done. In  $8T(\frac{n}{2})+3\cdot 2n+(4+2+1)3$ , i and j would be equal to 3.

We set the upper bound for i to  $\log n$ , insert this for i and can then calculate the asymptotic bound for the function, which is  $\Theta(n \log n)$ .

### Substitution method

```
T(n) = 4T(n/2) + n (recurrence)

<= 4c(n/2)^3 + n (inductive hyp.)

= cn^3/2 + n (simplification)

= cn^3 - (cn^3/2 - n) (rearrangement)

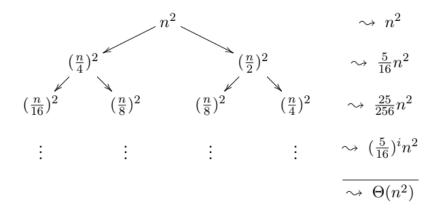
<= cn^3 (for c >= 2, n >= 1)
```

We assume an inductive hypothesis, in this example we assume that  $T(n) = n^3$ . We then check if our hypothesis is true.

#### Recursion trees

We visualize the recursion tree to see what happens when the recurrence is

Example for  $T(n) = T(n/4) + T(n/2) + n^2$ 



#### Master method

# Decreasing recurrences

Few examples:

$$T(n) = T(n-1) + 1 \to O(n)$$

$$T(n) = T(n-1) + n \to O(n^2)$$

$$T(n) = T(n-1) + \log n \to O(n \log n)$$

$$T(n) = 2T(n-1) + 1 \to O(2^n)$$

$$T(n) = 3T(n-1) + 1 \rightarrow O(3^n)$$

$$T(n) = 2T(n-1) + n \to O(n \cdot 2^n)$$

What we are seeing here, can be declared into a formula:

$$T(n) = a \cdot T(n-b) + f(n)$$
, where  $a, b > 0$  and  $f(n) = O(n^k), k \ge 0$ 

Furthermore, we apply following rules:

- $\begin{array}{ll} \bullet & a < 1 = O(n^k) = O(f(n)) \\ \bullet & a = 1 = O(n^{k+1}) = O(n \cdot f(n)) \\ \bullet & a > 1 = O(n^k \cdot a^{\frac{n}{b}}) = O(f(n) \cdot a^{\frac{n}{b}}) \end{array}$

# Case 1, 2 and 3

$$T(n) = \alpha \cdot T(n/6) + f(n)$$

$$\frac{a > 1}{b > 1} + f(n) = O(n^{k} \cdot \log^{k} n)$$

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