

COMP 555 Bioalgorithms



Fall 2014

Lecture 3: Algorithms and Complexity



Study Chapter 2.1-2.8

Topics



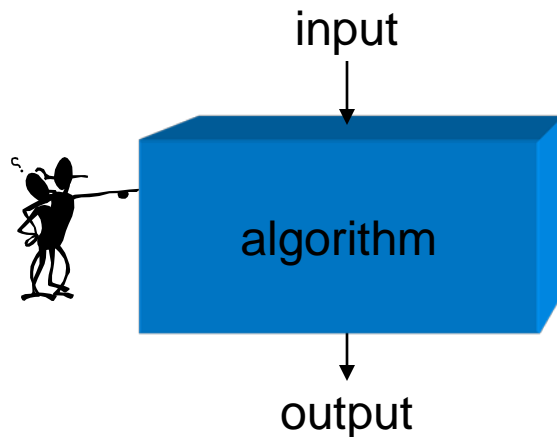
- Algorithms
 - Correctness
 - Complexity
- Some algorithm design strategies
 - Exhaustive
 - Greedy
 - Recursion
- Asymptotic complexity measures



What is an algorithm?



- An **algorithm** is a sequence of instructions that one must perform in order to solve a well-formulated **problem**.



Problem: Complexity

Algorithm: Correctness
Complexity



Problem: US Coin Change

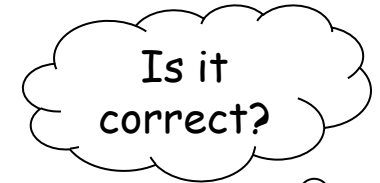


- Input
 - an amount of money
 $0 \leq M < 100$ in cents

- Output:
 - M cents in US coins using the minimal number of coins

- Example

72 cents



Two quarters



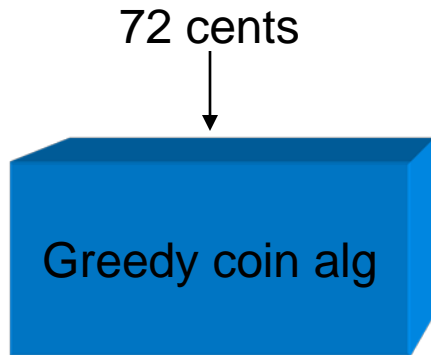
Two dimes



Two pennies



Algorithm 1: Greedy strategy



Use large denominations
as long as possible



Two quarters, 22 cents left



Two dimes, 2 cents left



Two pennies

Algorithm
description

$$r \leftarrow M$$

$$q \leftarrow \lfloor r / 25 \rfloor$$

$$r \leftarrow r - 25 \cdot q$$

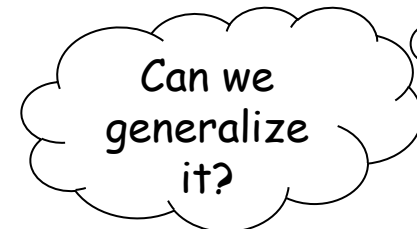
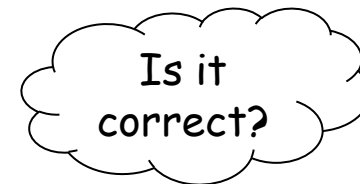
$$d \leftarrow \lfloor r / 10 \rfloor$$

$$r \leftarrow r - 10 \cdot d$$

$$n \leftarrow \lfloor r / 5 \rfloor$$

$$r \leftarrow r - 5 \cdot n$$

$$p \leftarrow r$$



Algorithm 2: Exhaustive strategy



- Enumerate *all* combinations of coins. Record the combination totaling to M with fewest coins
 - *All* is impossible. Limit the multiplicity of each coin!
 - First try (80,000 combinations)

coin	Quarter	Dime	Nickel	Penny
multiplicity	0..3	0..9	0..19	0..99

- Better (200 combinations)

coin	Quarter	Dime	Nickel	Penny
multiplicity	0 .. 3	0 .. 4	0 .. 1	0 .. 4



Is it correct?



Correctness



- An algorithm is **correct** only if it produces correct result for all input instances.
 - If the algorithm gives an incorrect answer for one or more input instances, it is an **incorrect** algorithm.
- US coin change problem
 - It is easy to show that the exhaustive algorithm is correct
 - The greedy algorithm is correct but we didn't really show it



Observations



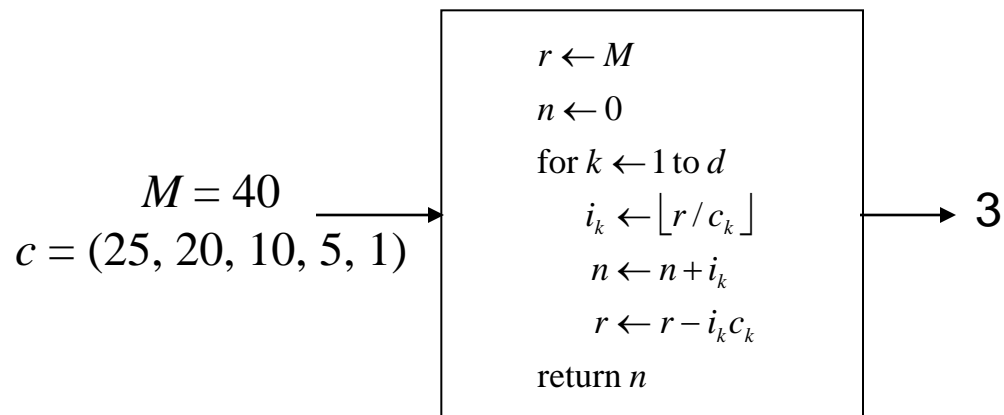
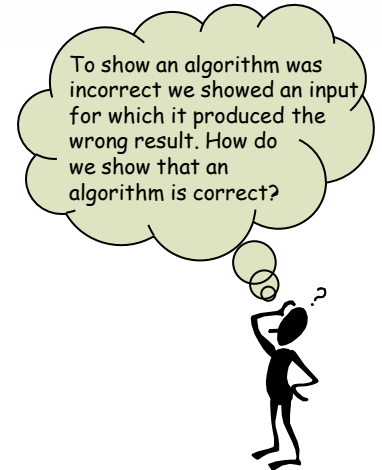
- Given a problem, there may be many **correct** algorithms.
 - They give identical outputs for the same inputs
 - They give the expected outputs for any valid input
- The **costs** to perform different algorithms may be different.
- US coin change problem
 - The exhaustive algorithm checks 200 combinations
 - The greedy algorithm performs just a few arithmetic operations



Change Problem: generalization



- Input:
 - an amount of money M
 - an array of denominations $c = (c_1, c_2, \dots, c_d)$ in order of decreasing value
- Output: the smallest number of coins



Incorrect algorithm!

The correct answer should be **2**.

Is it correct?



How to Compare Algorithms?



- **Complexity** – the cost of an algorithm can be measured in either time and space
 - Correct algorithms may have different complexities.
- How do we assign “cost” for time?
 - Roughly proportional to number of instructions performed by computer
 - Exact cost is difficult to determine and not very useful
 - Varies with computer, particular input, etc.
- How to analyze an algorithm’s complexity
 - Depends on algorithm design



Recursive Algorithms



- Recursion is an algorithm design technique for solving problems in terms of simpler subproblems
 - The simplest versions, called base cases, are merely declared.
 - Recursive definition:** $\text{factorial}(n) = n \times \text{factorial}(n - 1)$
 - Base case:** $\text{factorial}(1) = 1$
 - Easy to analyze
- Thinking recursively...



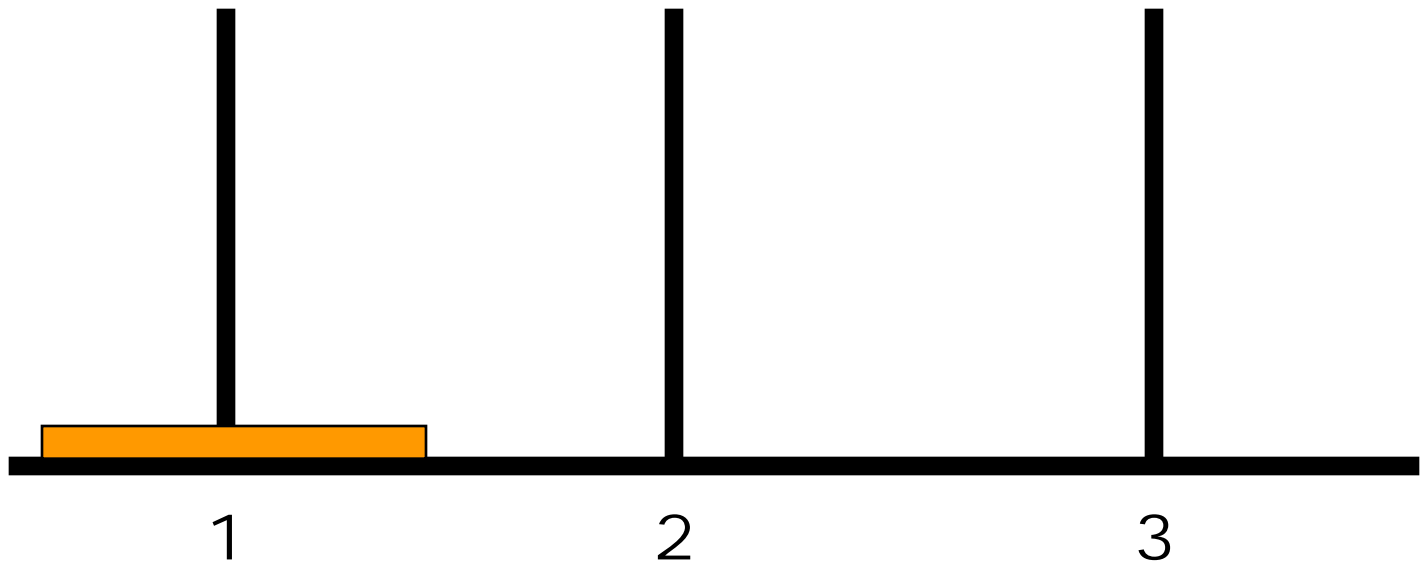
Towers of Hanoi



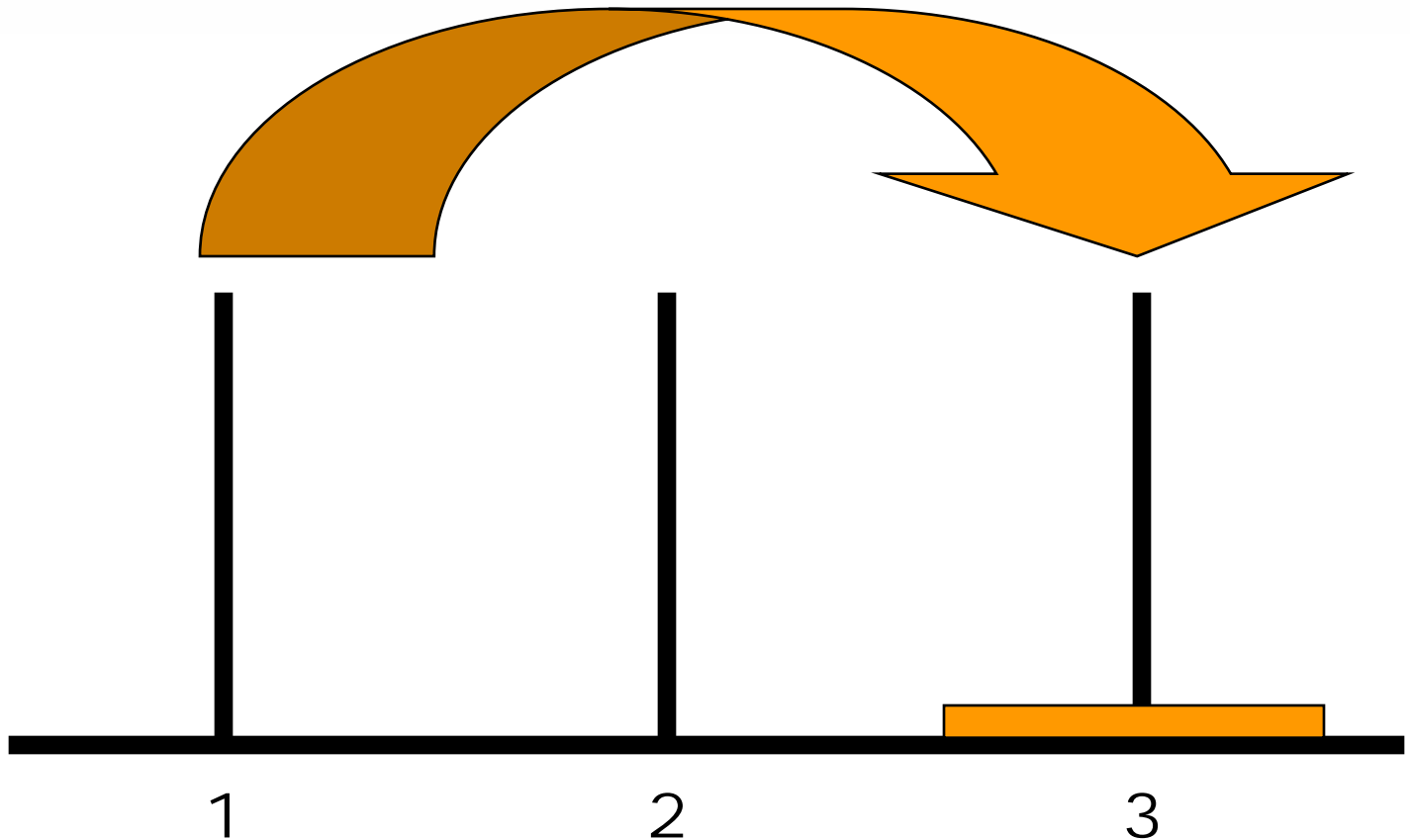
- There are three pegs and a number of disks with decreasing radii (smaller ones on top of larger ones) stacked on Peg 1.
- Goal: move all disks to Peg 3.
- Rules:
 - When a disk is moved from one peg it must be placed on another peg.
 - Only one disk may be moved at a time, and it must be the top disk on a tower.
 - A larger disk may never be placed upon a smaller disk.



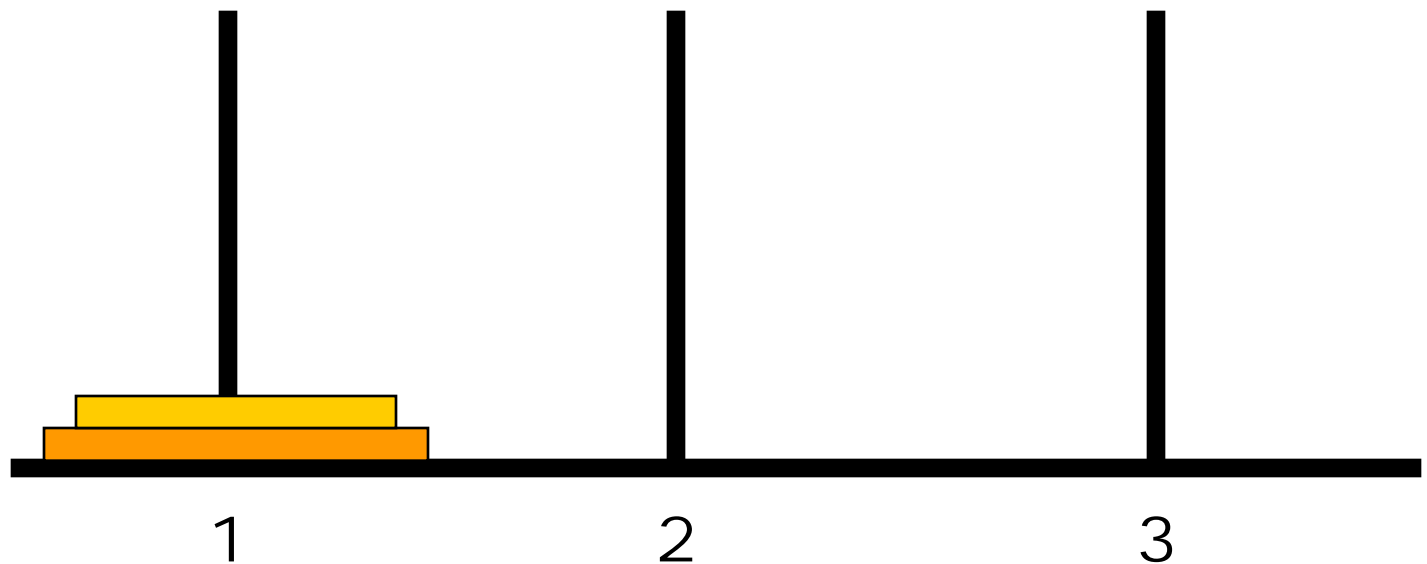
A single disk tower



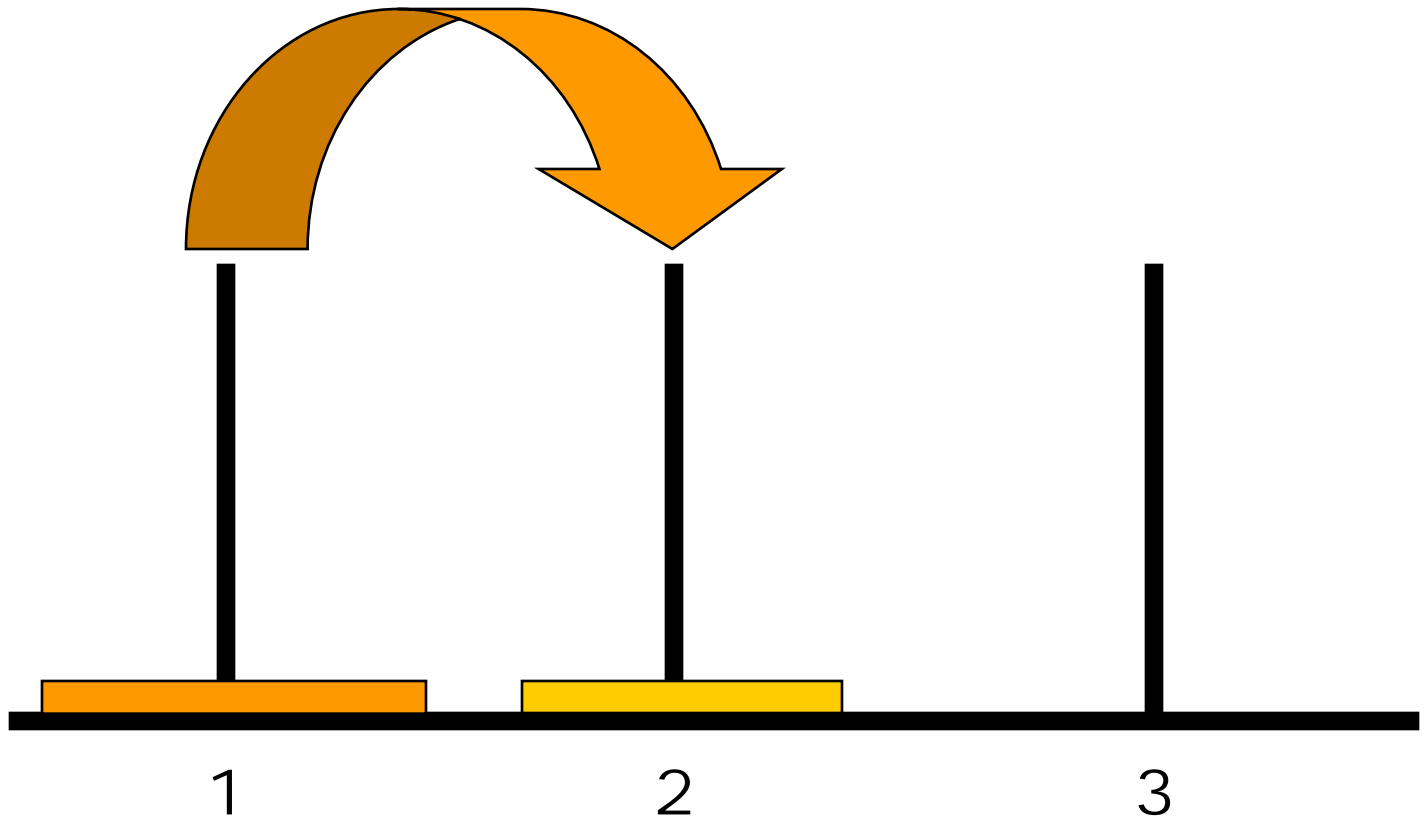
A single disk tower



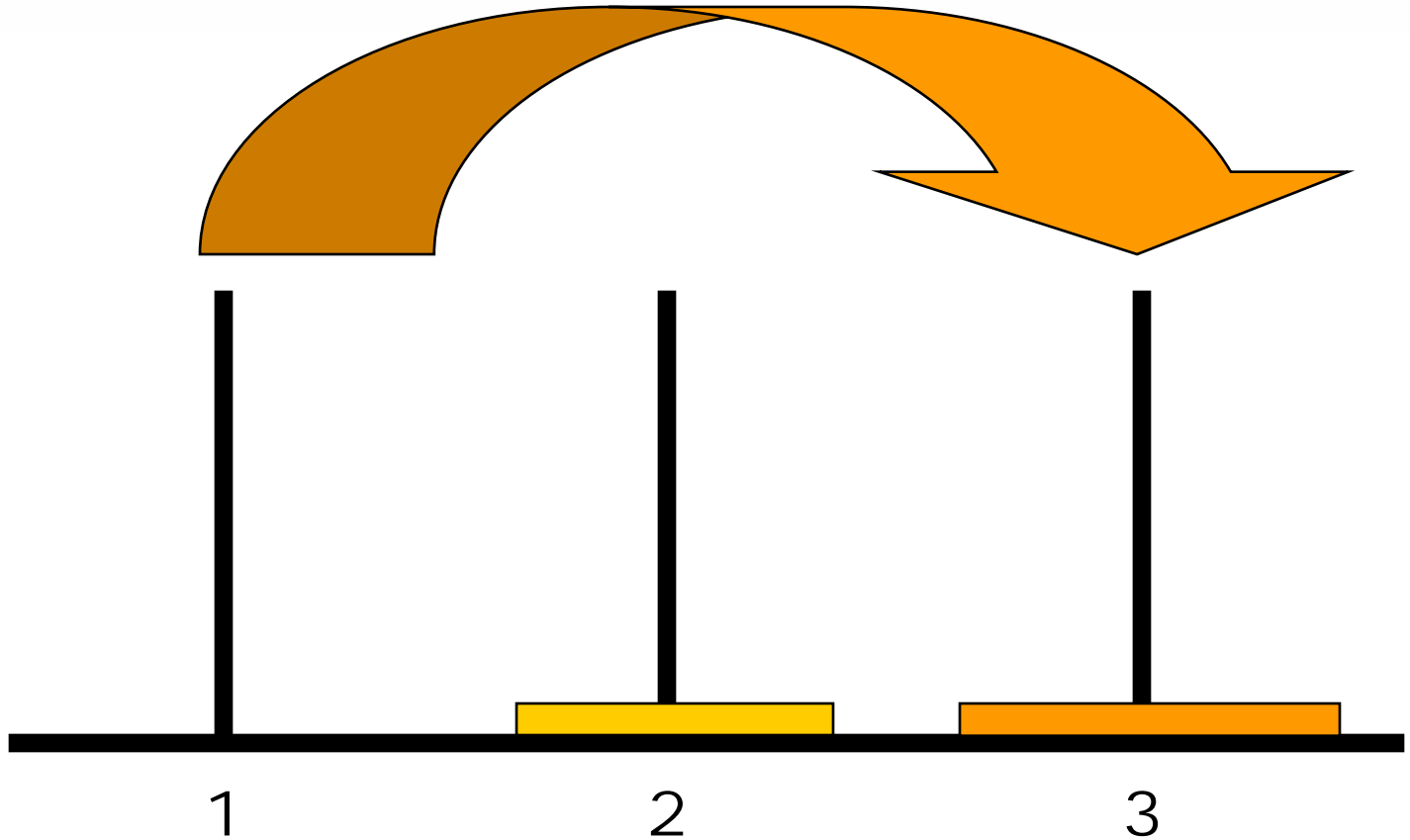
A two disk tower



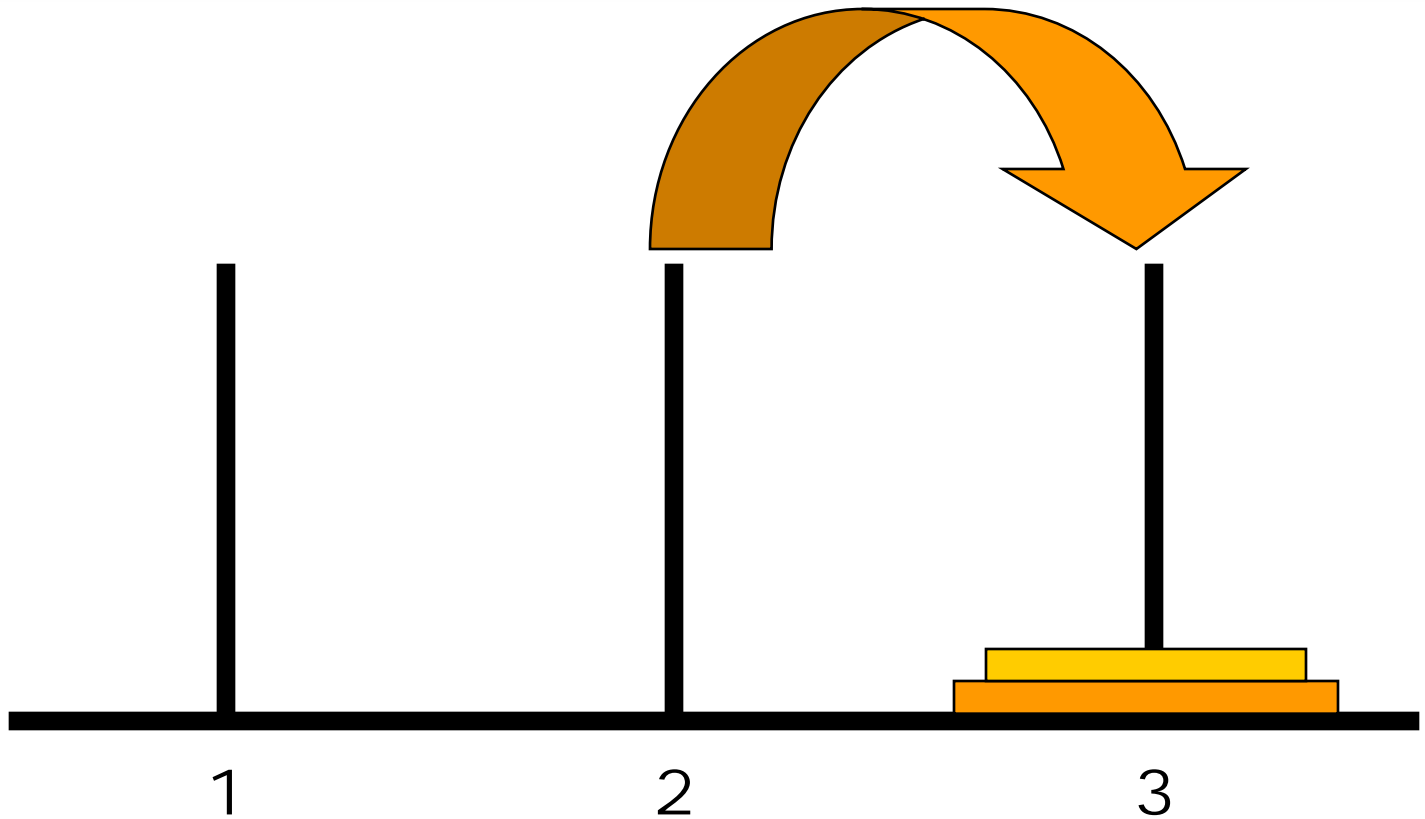
Move 1



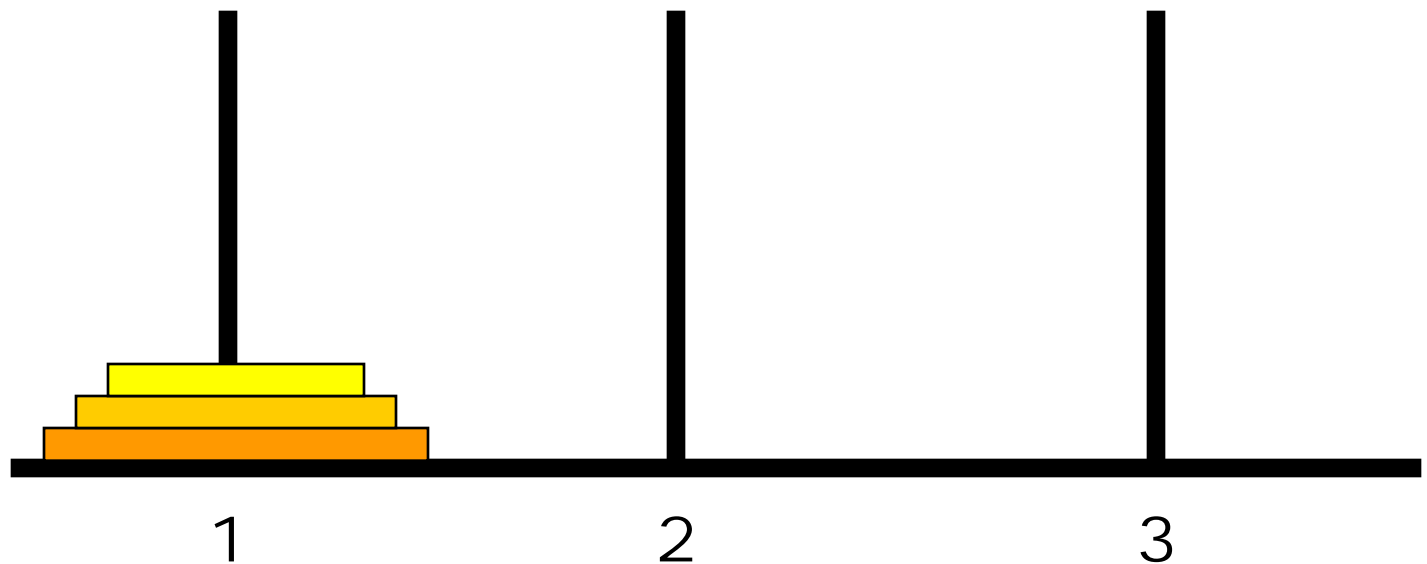
Move 2



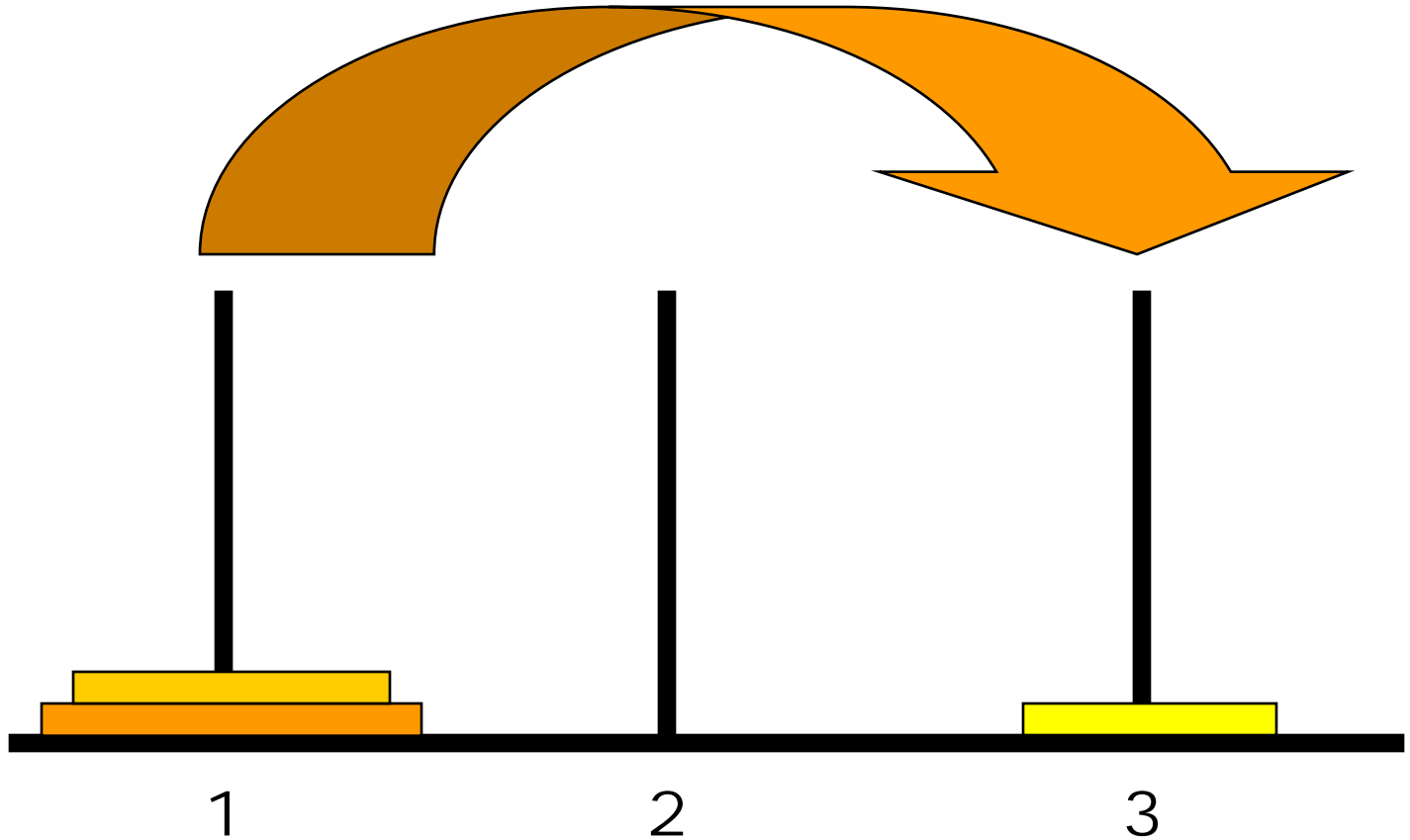
Move 3



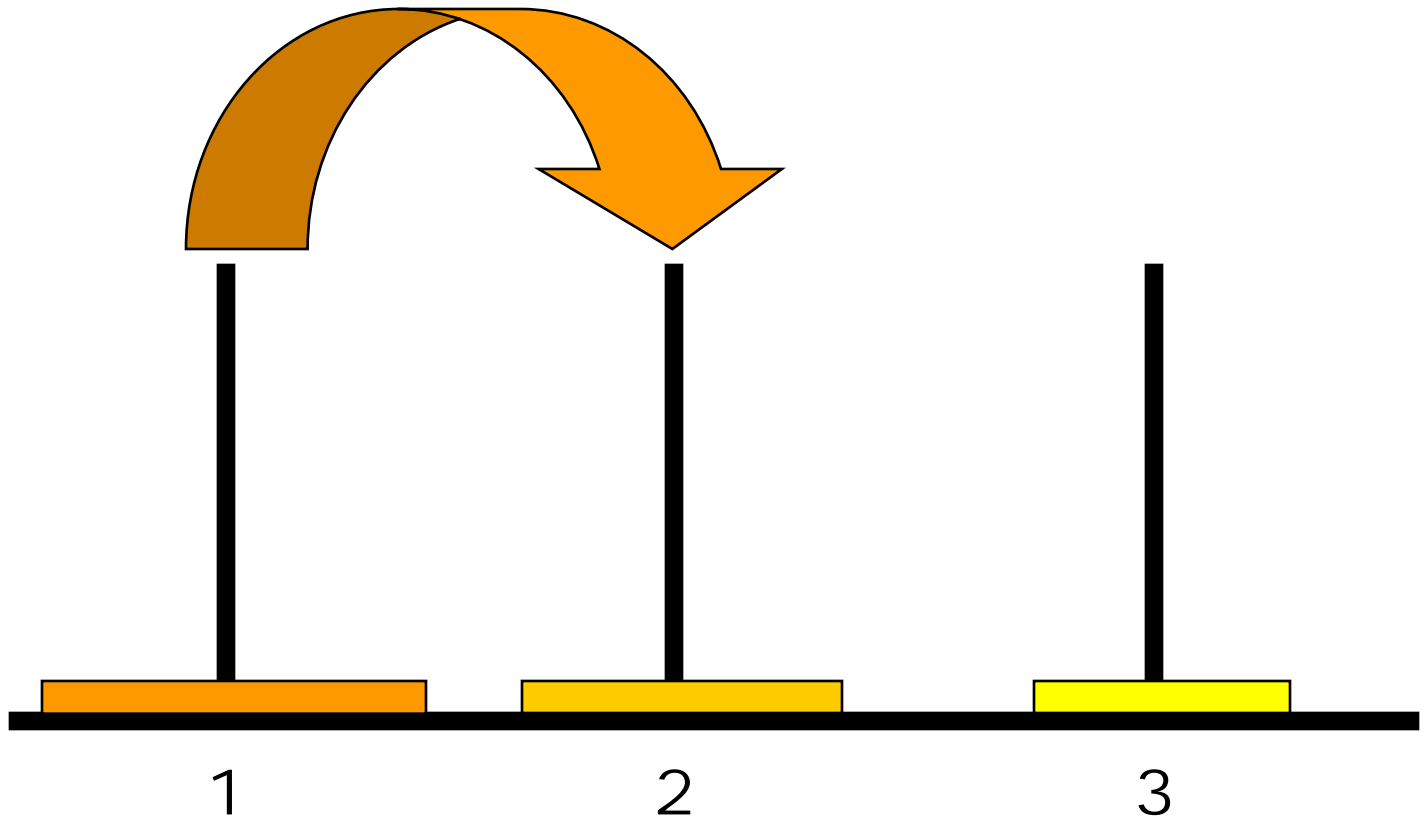
A three disk tower



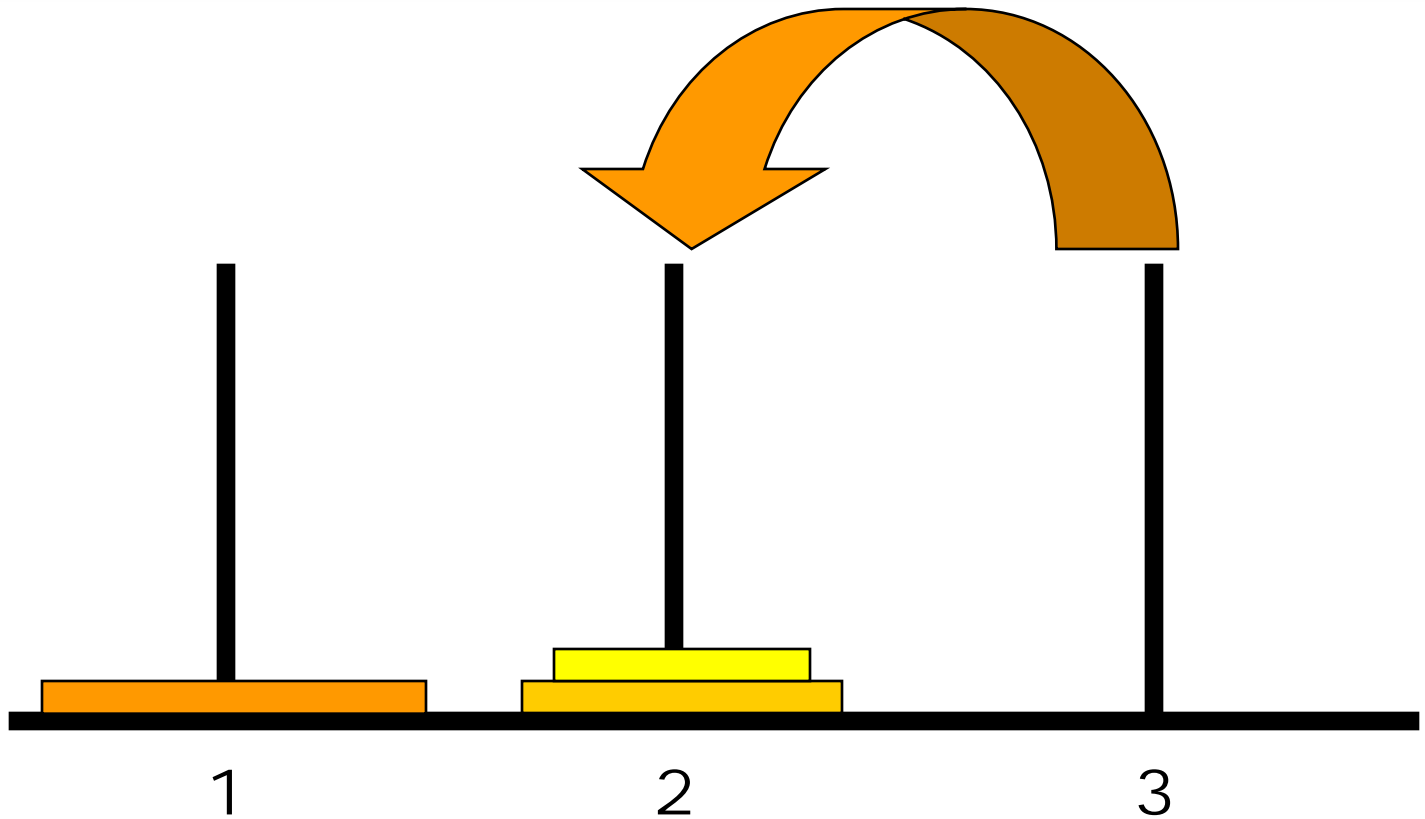
Move 1



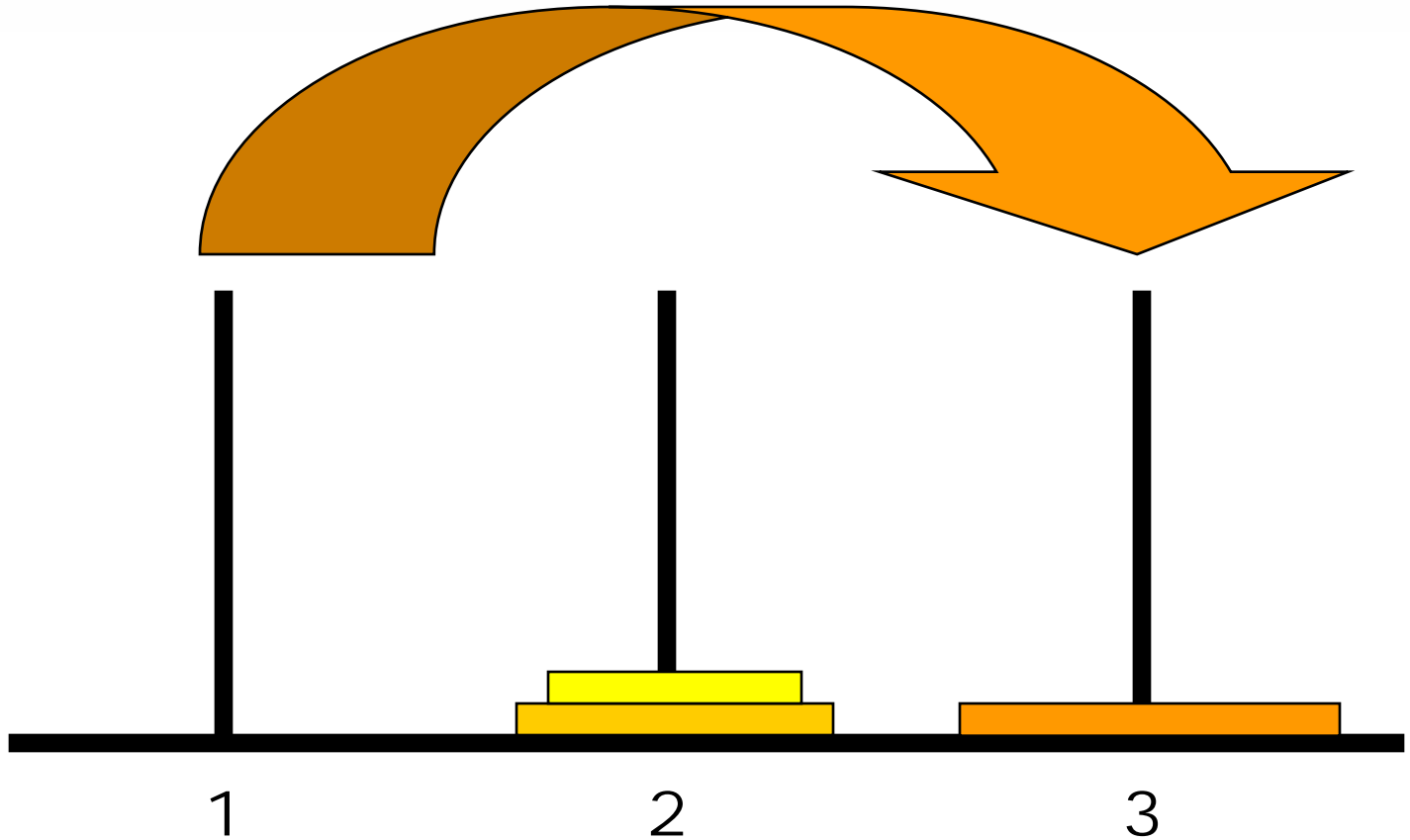
Move 2



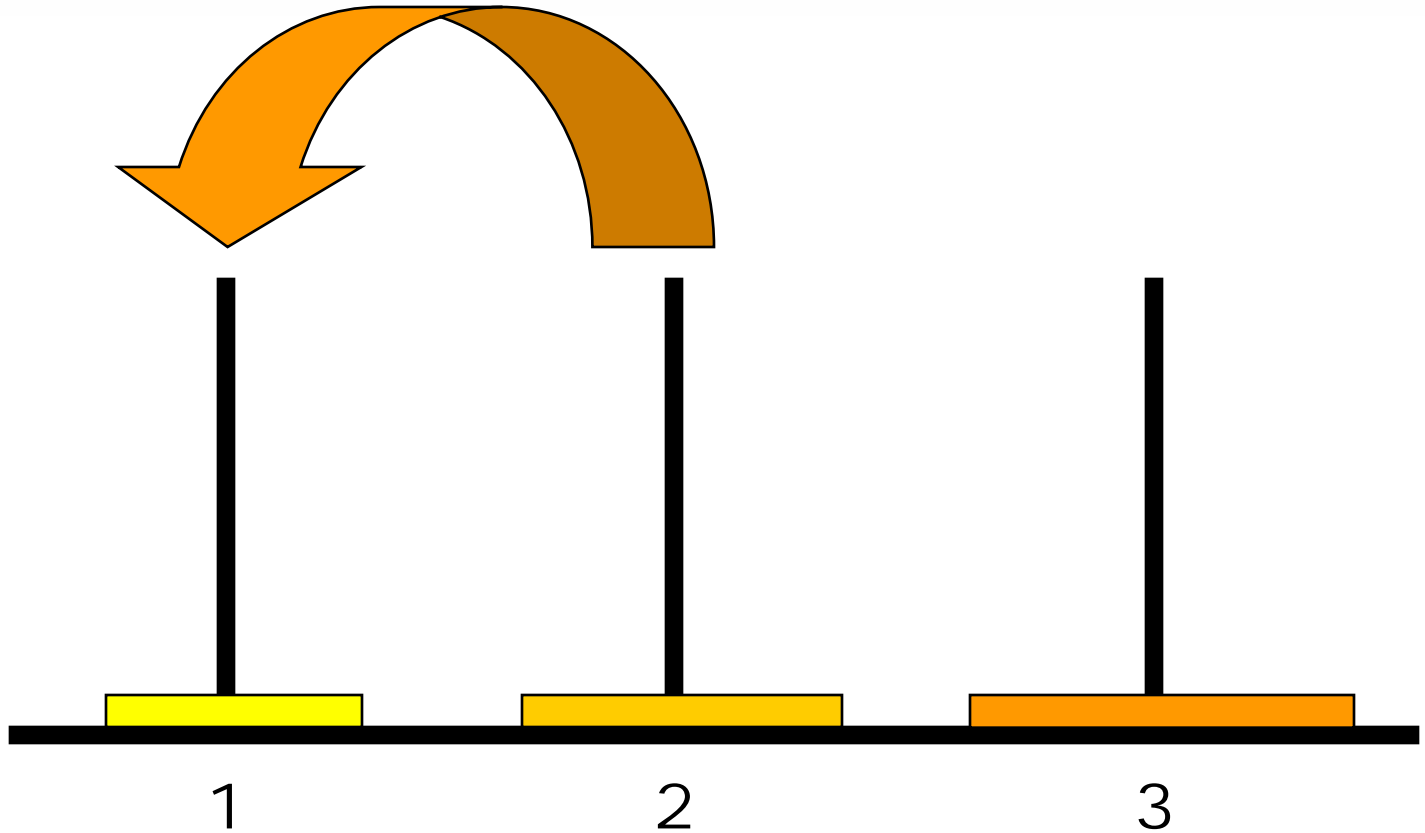
Move 3



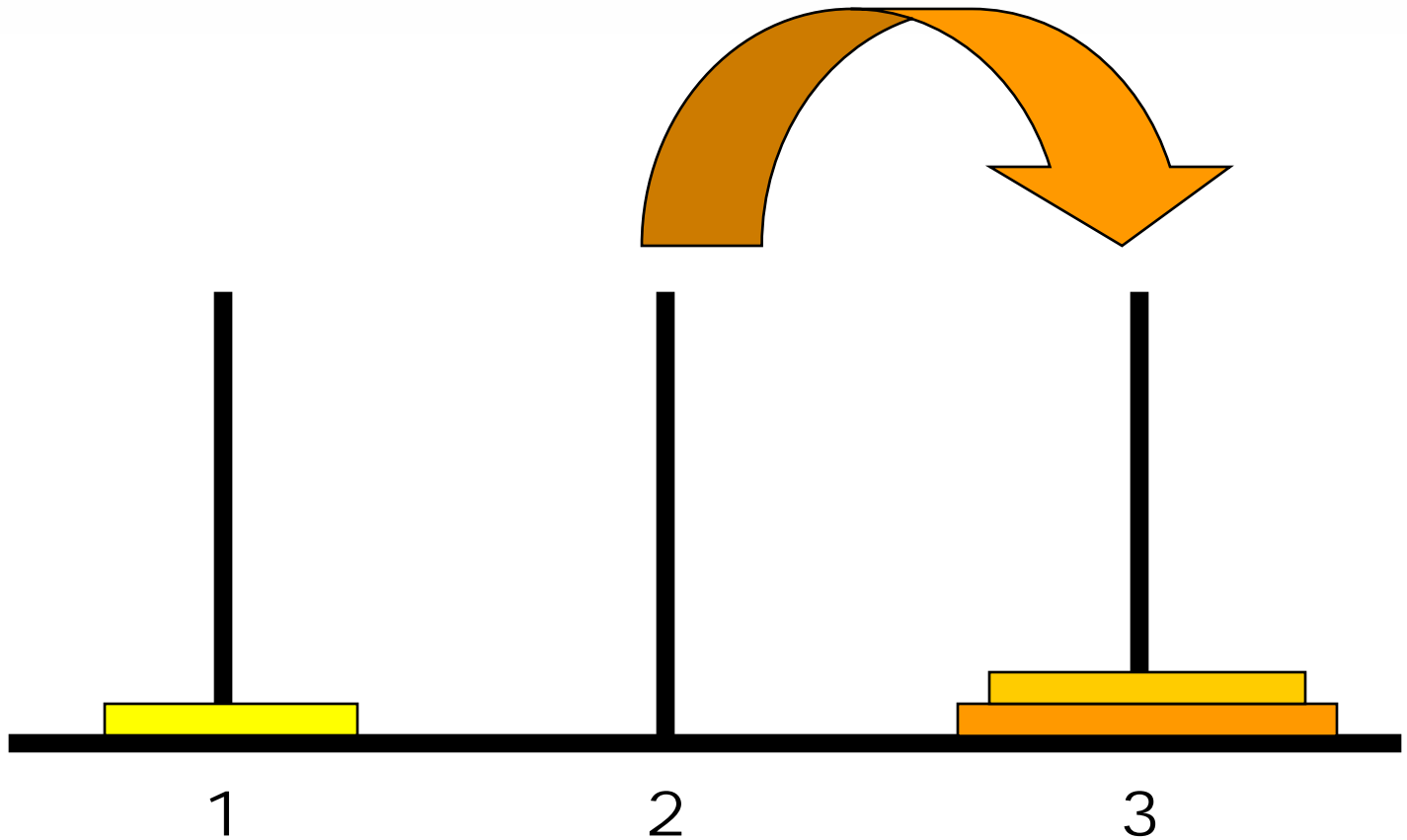
Move 4



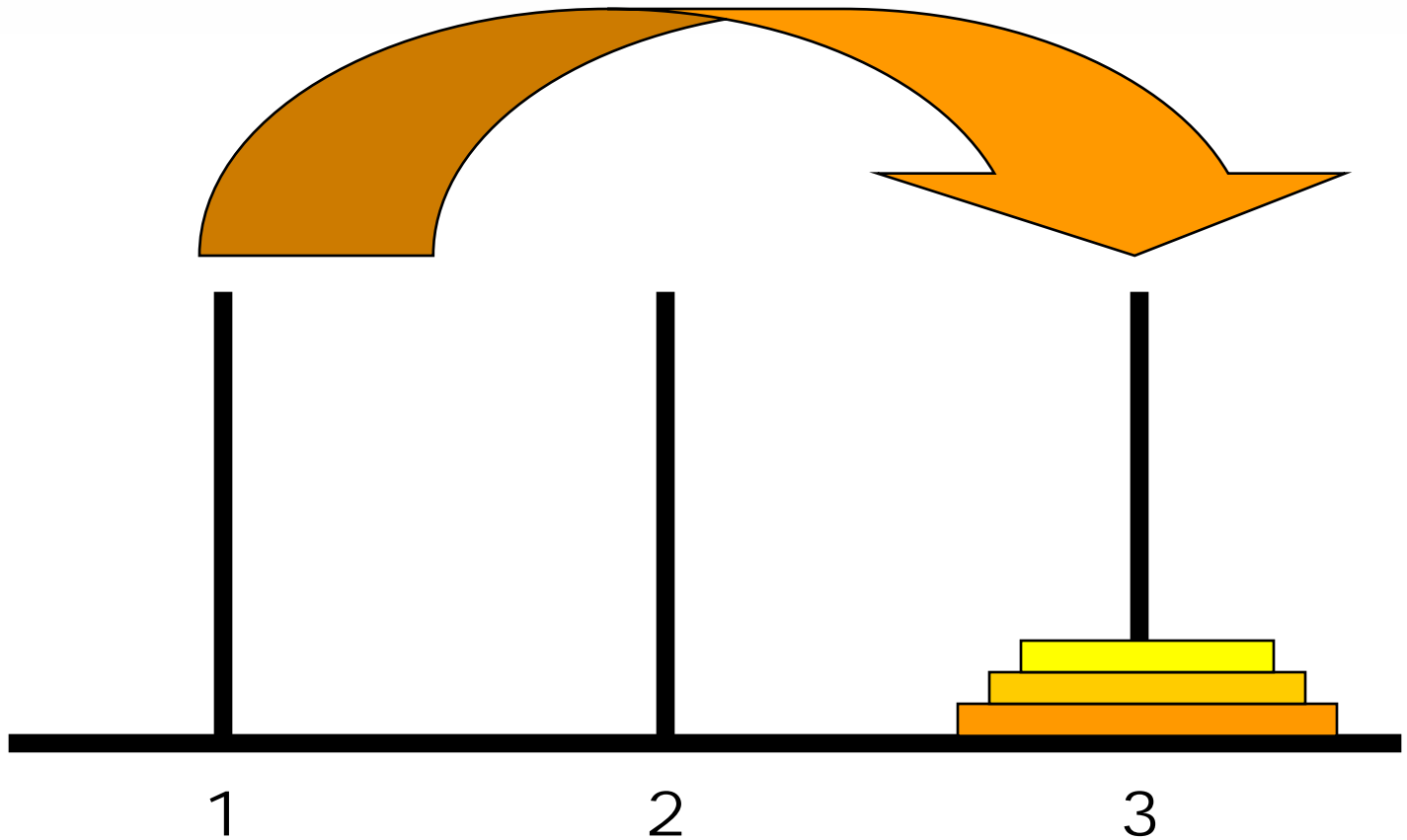
Move 5



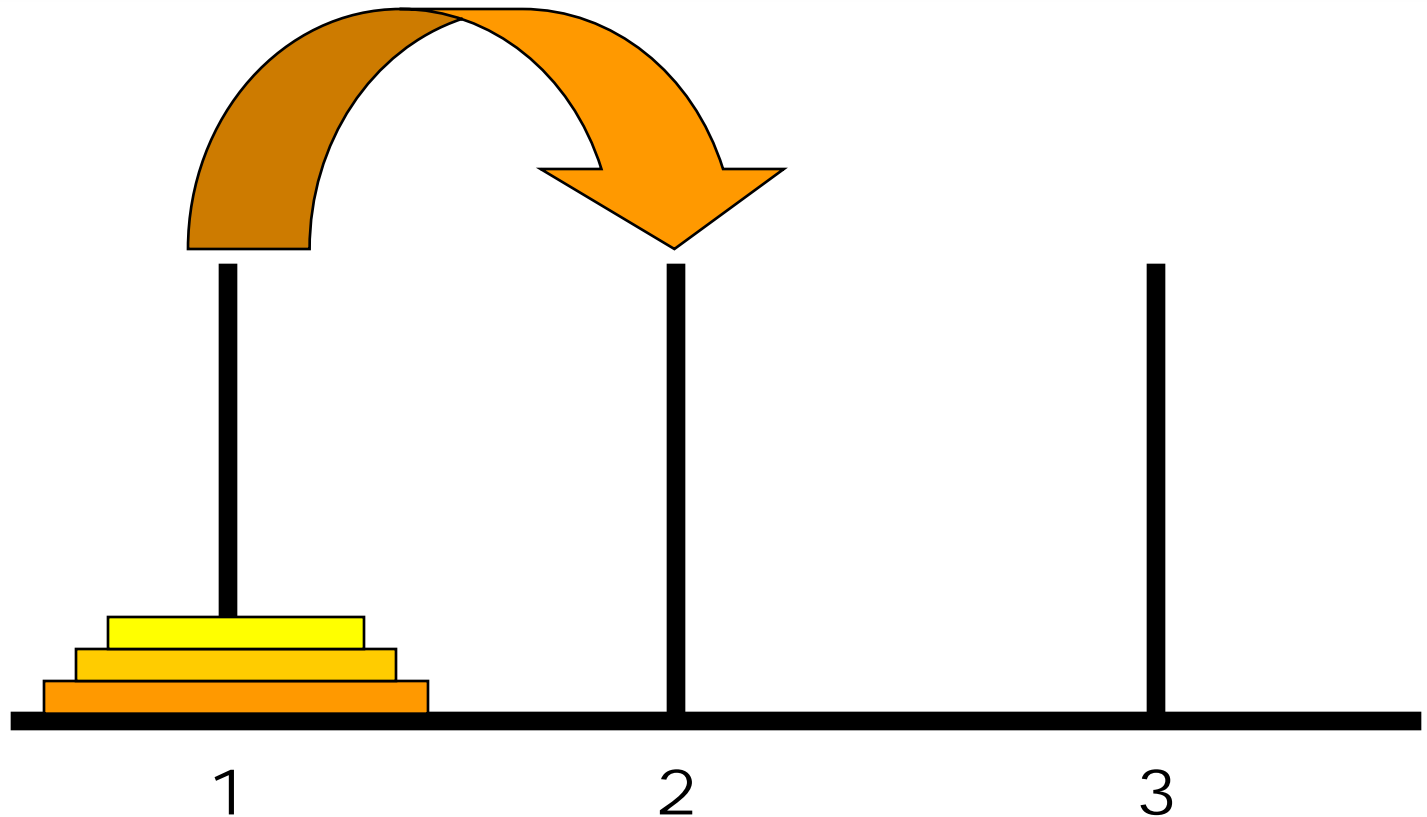
Move 6



Move 7



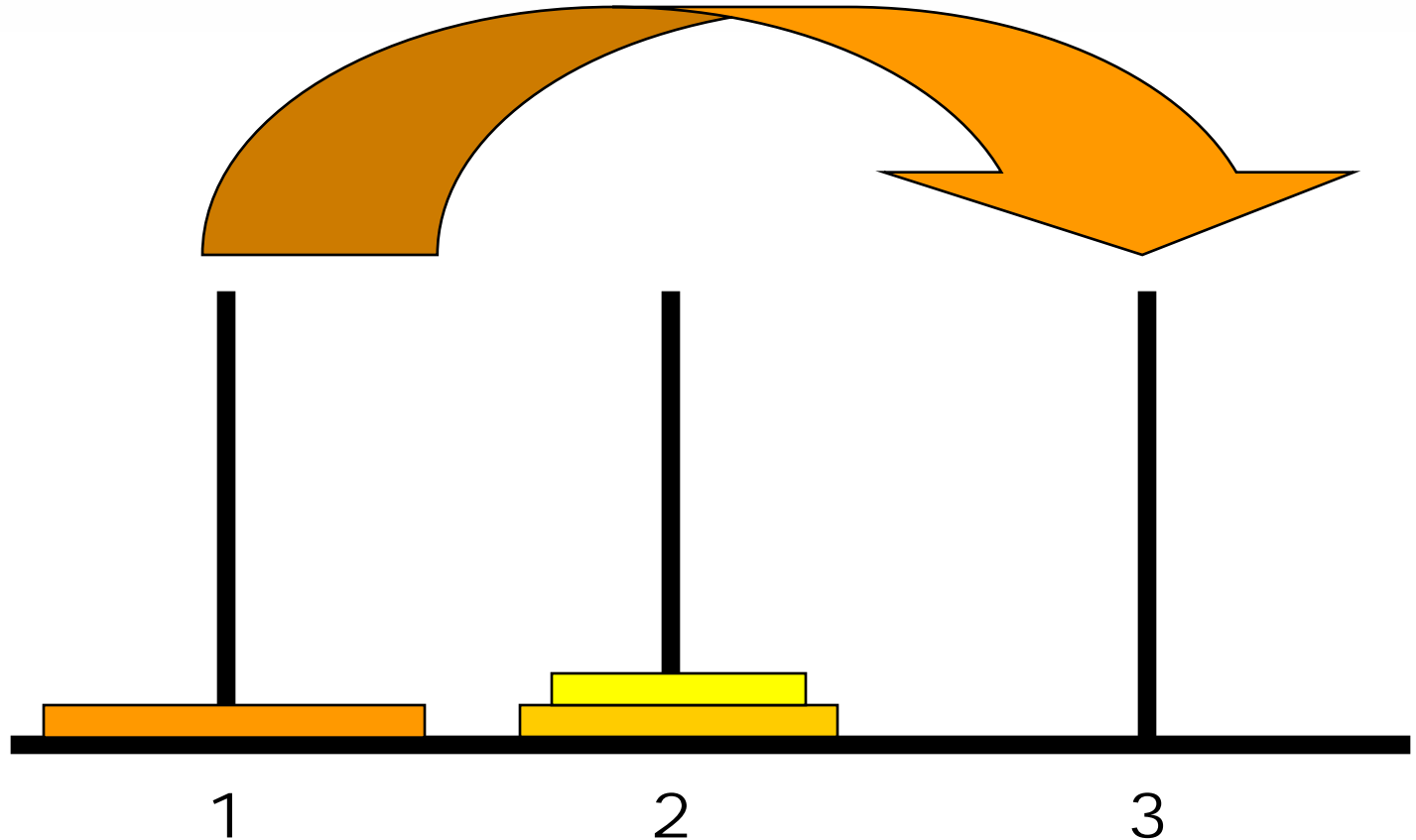
Simplifying the algorithm for 3 disks



- Step 1. Move the top 2 disks from 1 to 2 using 3 as intermediate



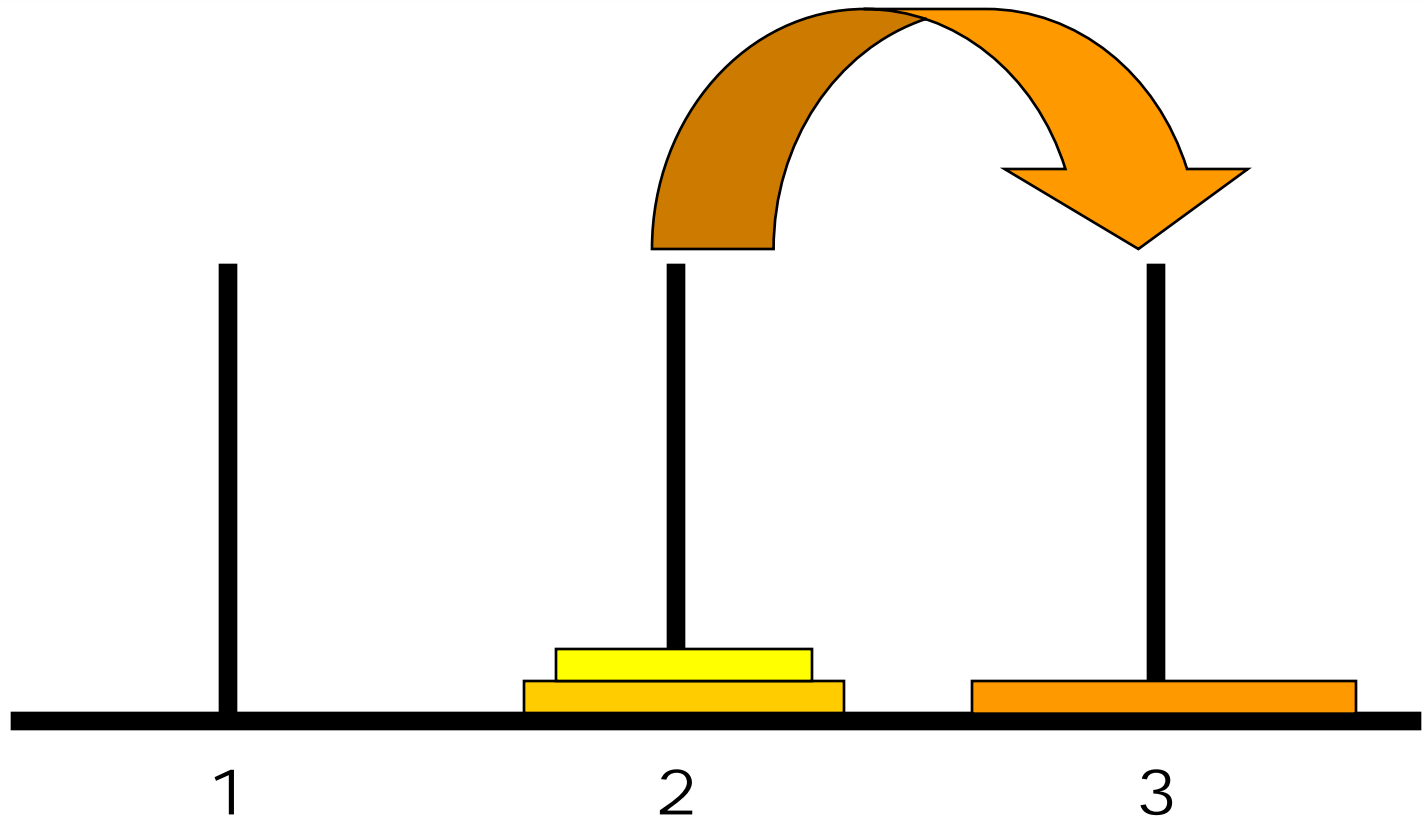
Simplifying the algorithm for 3 disks



- Step 2. Move the remaining disk from 1 to 3



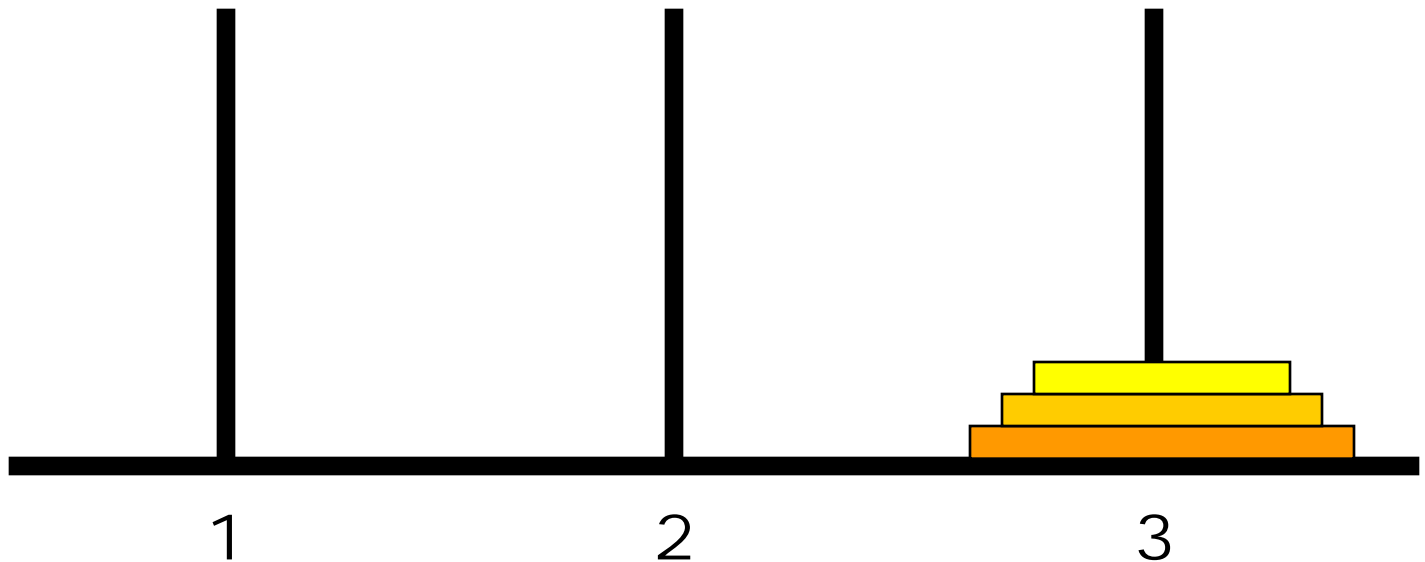
Simplifying the algorithm for 3 disks



- Step 3. Move 2 disks from 2 to 3 using 1 as intermediate



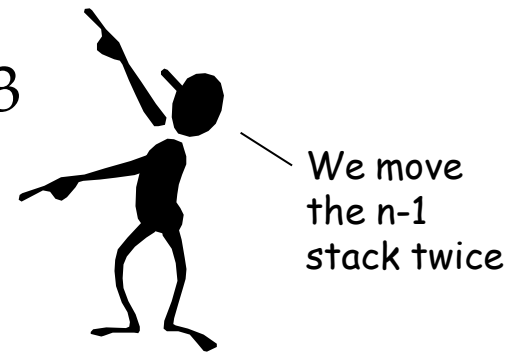
Simplifying the algorithm for 3 disks



The problem for N disks becomes



- A base case of a one-disk move.
- A recursive step for moving $n-1$ disks.
- To move n disks from Peg 1 to Peg 3, we need to
 - Move $(n-1)$ disks from Peg 1 to Peg 2
 - Move the n^{th} disk from Peg 1 to Peg 3
 - Move $(n-1)$ disks from Peg 2 to Peg 3
 - The number of disk moves is



$$T(1) = 1$$

$$T(n) = 2T(n-1) + 1 = 2^n - 1$$

Exponential algorithm



Towers of Hanoi



- If you play Hanoi Towers with . . . it takes . . .
 - 1 disk ... 1 move
 - 2 disks ... 3 moves
 - 3 disks ... 7 moves
 - 4 disks ... 15 moves
 - 5 disks ... 31 moves
 - .
 - .
 - .
 - 20 disks ... 1,048,575 moves
 - 32 disks ... 4,294,967,295 moves



Sorting



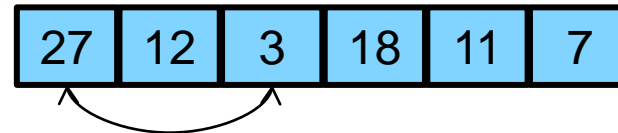
- A very common problem is to arrange data into either ascending or descending order
 - Viewing, printing
 - **Faster to search, find min/max, compute median/mode, etc.**
- Lots of sorting algorithms
 - From the simple to very complex
 - **Some optimized for certain situations (lots of duplicates, almost sorted, etc.)**



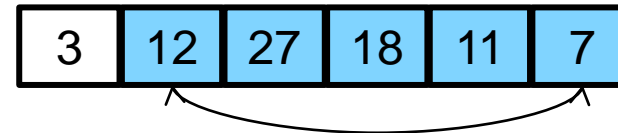
Selection Sort



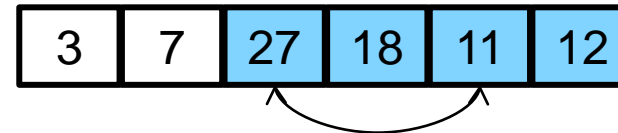
Find the smallest element and swap it with the first:



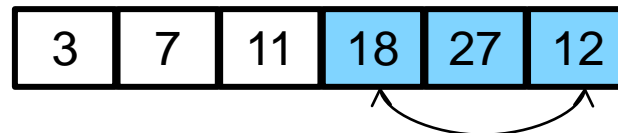
Find the next smallest element and swap it with the second:



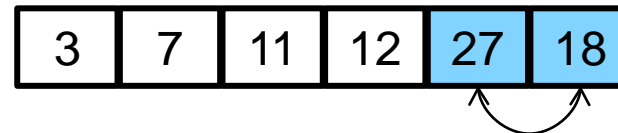
Do the same for the third element:



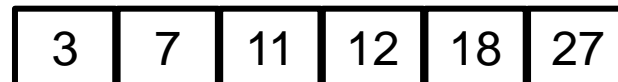
And the fourth:



Finally, the fifth:



Completely sorted:



“In-place” sort



Selection sort



```
def selectionSortRecursive(a,first,last):  
    if (first < last):  
        index = indexOfMin(a,first,last)  
        temp = a[index]  
        a[index] = a[first]  
        a[first] = temp  
        a = selectionSortRecursive(a,first+1,last)  
    return a
```

$(n - 1)$ swaps

Quadratic in time

$$\frac{n(n-1)}{2} - 1 \text{ comparisons}$$

```
def indexOfMin(arr,first,last):  
    index = first  
    for k in xrange(index+1,last):  
        if (arr[k] < arr[index]):  
            index = k  
    return index
```



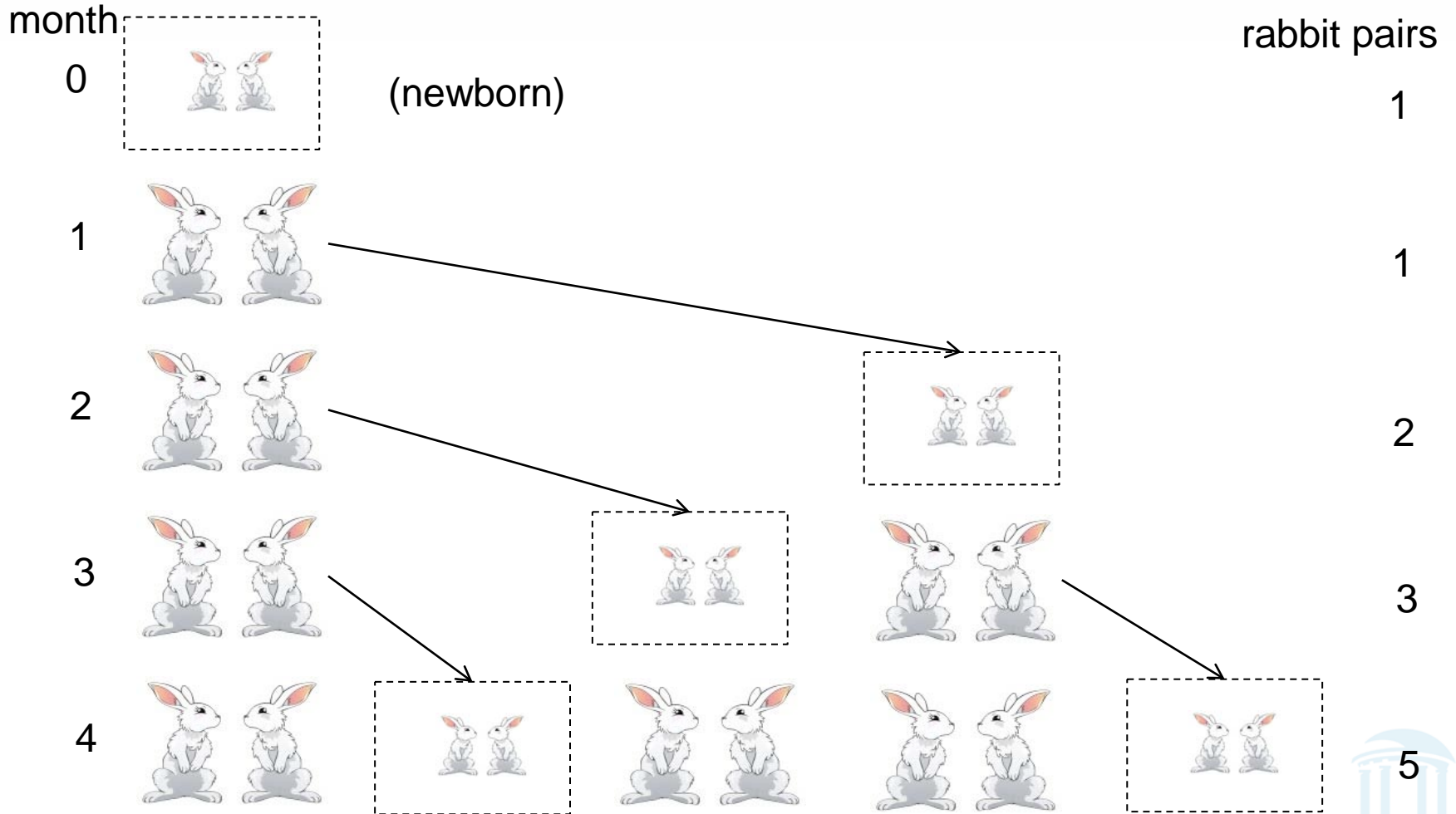
Year 1202: Leonardo Fibonacci



- He asked the following question:
 - How many pairs of rabbits are produced from a single pair in n months if every month each pair of rabbits more than 1 month old produces a new pair?
 - Here we assume that each pair born has one male and one female and breeds indefinitely
 - The initial pair at month 0 are newborns
 - Let $f(n)$ be the number of rabbit pairs present at the beginning of month n



Fibonacci Number



Fibonacci Number



- Clearly, we have:
 - $f(0) = 1$ (the original pair, as newborns)
 - $f(1) = 1$ (still the original pair because newborns need to mature a month before they reproduce)
 - $f(n) = f(n-1) + f(n-2)$ in month n we have
 - the $f(n-1)$ rabbit pairs present in the previous month, and
 - newborns from the $f(n-2)$ rabbit pairs present 2 months earlier
 - f : 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, ...
 - The solution for this recurrence is ($n > 0$):

$$f(n) = \frac{1}{\sqrt{5}} \left(\left(\frac{1+\sqrt{5}}{2} \right)^n - \left(\frac{1-\sqrt{5}}{2} \right)^n \right)$$

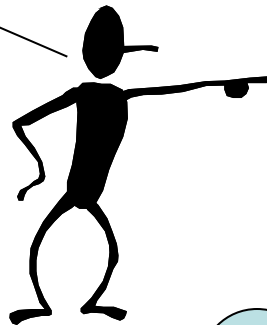


Fibonacci Number

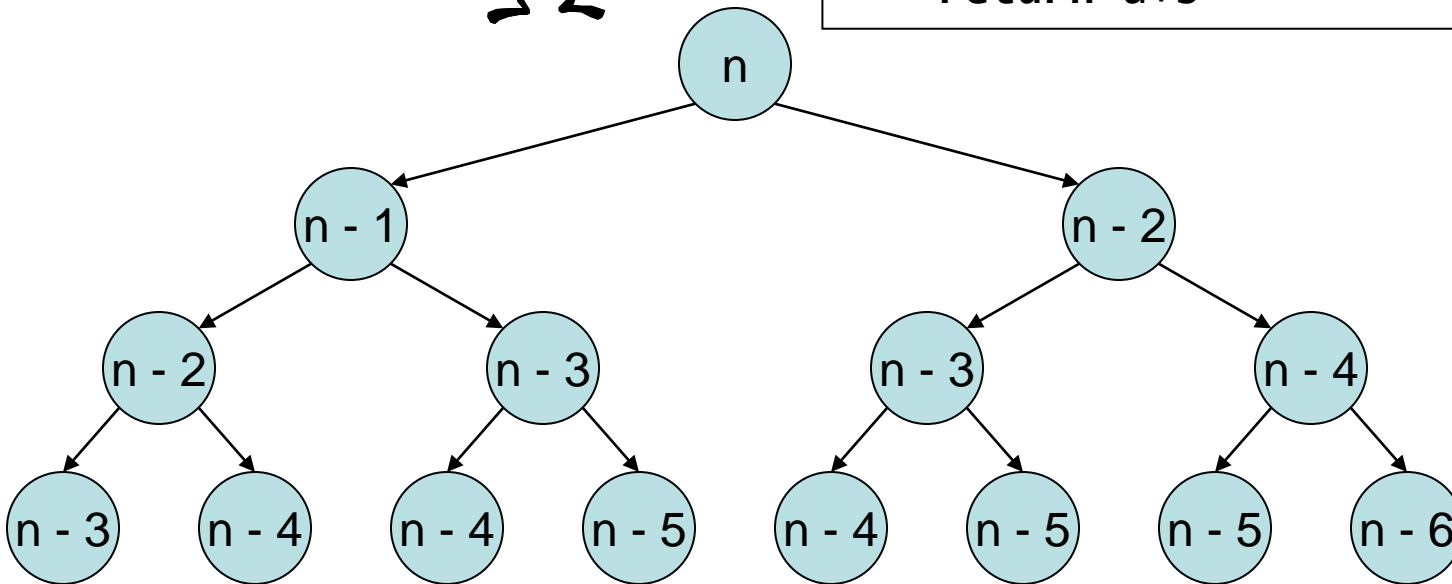


Recursive Algorithm

Exponential time!



```
def fibonacciRecursive(n):  
    if (n <= 1):  
        return 1  
    else:  
        a = fibonacciRecursive(n-1)  
        b = fibonacciRecursive(n-2)  
    return a+b
```

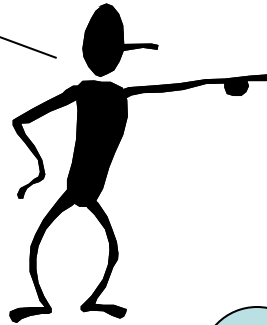


Fibonacci Number

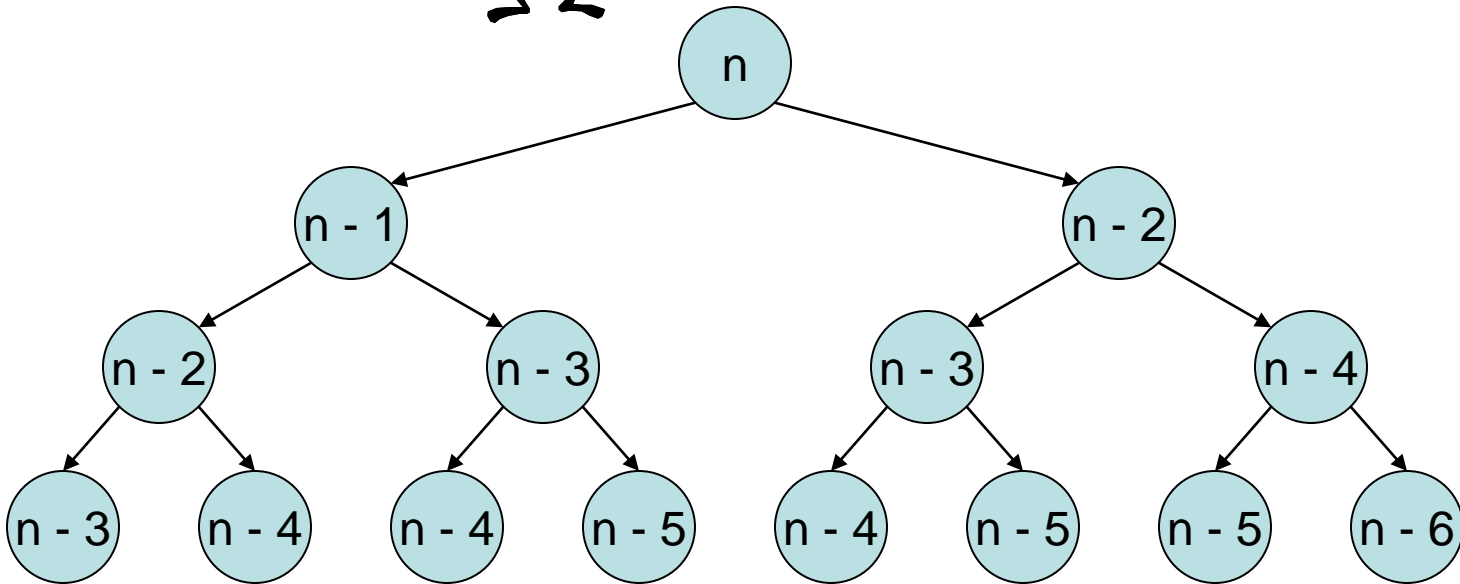


Linear time!

Iterative
Algorithm



```
def fibonacciIterative(n):  
    f0, f1 = 1, 1  
    for i in xrange(0,n):  
        f0, f1 = f1, f0 + f1  
    return f0
```



Orders of magnitude



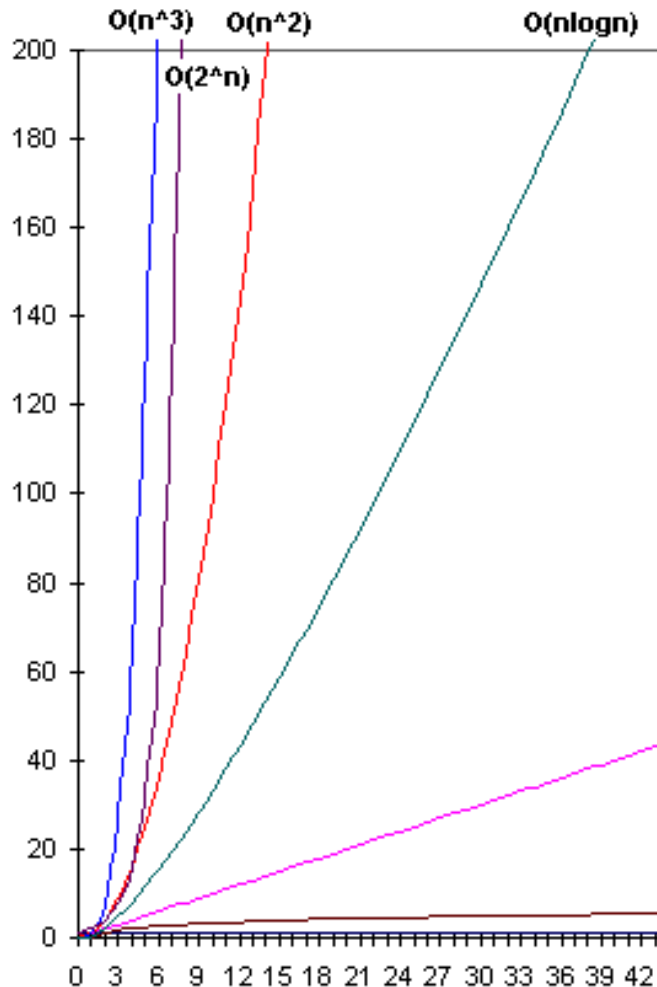
- 10^1
- 10^2 Number of students in computer science department
- 10^3 Number of students in the college of art and science
- 10^4 Number of students enrolled at UNC
- ...
- ...
- 10^{10} Number of stars in the galaxy
- 10^{20} Total number of all stars in the universe
- 10^{80} Total number of particles in the universe
- $10^{100} \ll$ Number of moves needed for 400 disks in the Towers of Hanoi puzzle
- Towers of Hanoi puzzle is *computable* but it is NOT feasible.



Is there a “real” difference?



- Growth of functions



n	1	lgn	n	n lgn	n ²	n ³	2 ⁿ
1	1	0.00	1	0	1	1	2
10	1	3.32	10	33	100	1,000	1024
100	1	6.64	100	664	10,000	1,000,000	1.2 x 10 ³⁰
1000	1	9.97	1000	9970	1,000,000	10 ⁹	1.1 x 10 ³⁰¹



Asymptotic Notation



- *Order of growth* is the interesting measure:
 - Highest-order term is what counts
 - As the input size grows larger it is the high order term that dominates
- Θ notation: $\Theta(n^2)$ = “this function grows similarly to n^2 ”.
- Big-O notation: $O(n^2)$ = “this function grows no faster than n^2 ”.
 - Describes an *upper bound*.



Big-O Notation



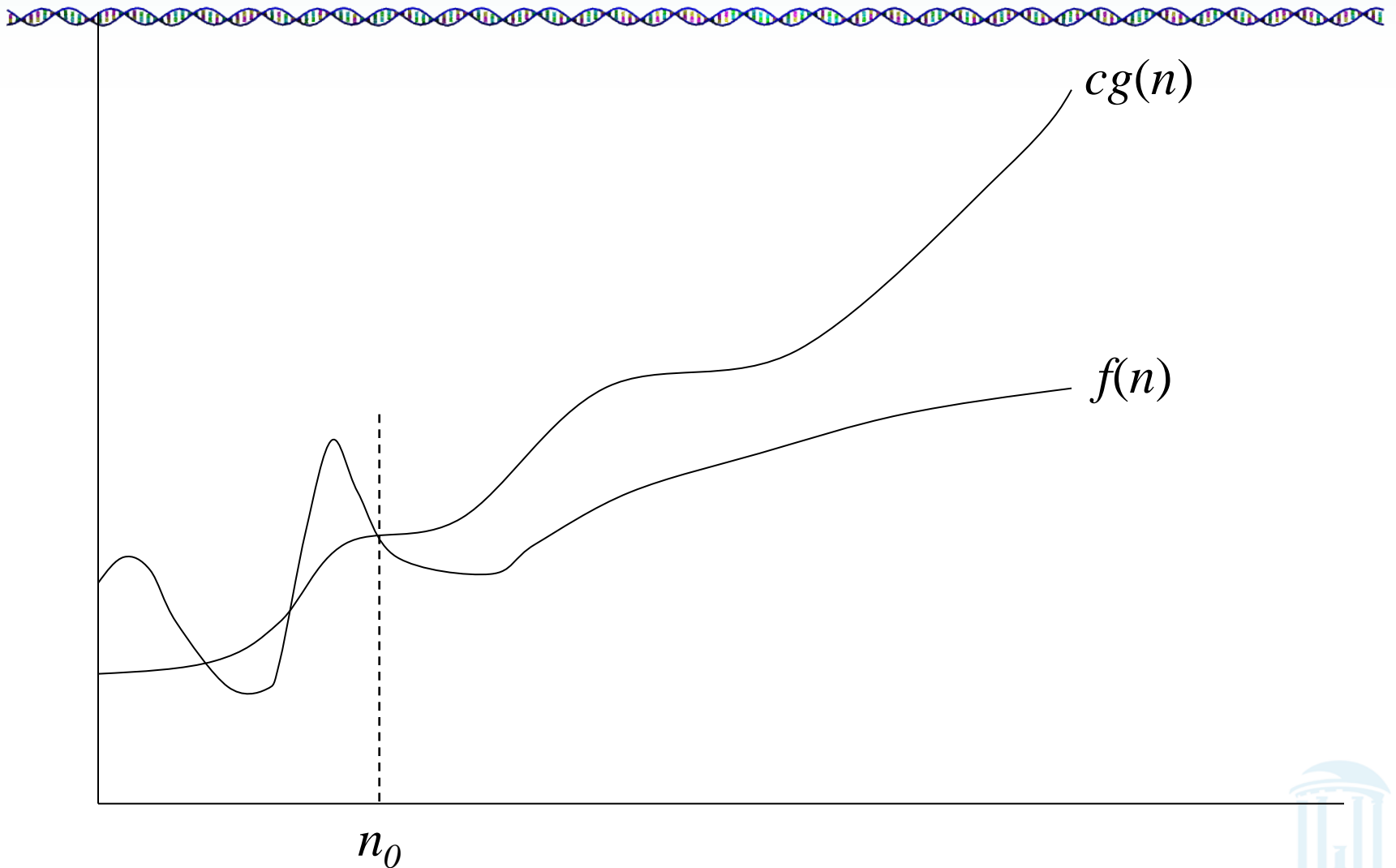
$f(n) = O(g(n))$: there exist positive constants c and n_0 such that

$$0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0$$

- What does it mean?
 - If $f(n) = O(n^2)$, then:
 - $f(n)$ can be larger than n^2 sometimes, **but...**
 - We can choose some constant c and some value n_0 such that for **every** value of n larger than n_0 : $f(n) < cn^2$
 - That is, for values larger than n_0 , $f(n)$ is never more than a constant multiplier greater than n^2
 - Or, in other words, $f(n)$ does not grow more than a constant factor faster than n^2 .



Visualization of $O(g(n))$



Big-O Notation



$$2n^2 = O(n^2)$$

$$1,000,000n^2 + 150,000 = O(n^2)$$

$$n^2 + 1,000,000n + 20 = O(n^2)$$

$$3n + 4 = O(n^2)$$

$$2n^3 + 2 \neq O(n^2)$$

$$n^{2.1} \neq O(n^2)$$



Big-O Notation



- Prove that: $20n^2 + 2n + 5 = O(n^2)$
- Let $c = 21$ and $n_0 = 4$
- $21n^2 > 20n^2 + 2n + 5$ for all $n > 4$
 $n^2 > 2n + 5$ for all $n > 4$

TRUE



Θ -Notation



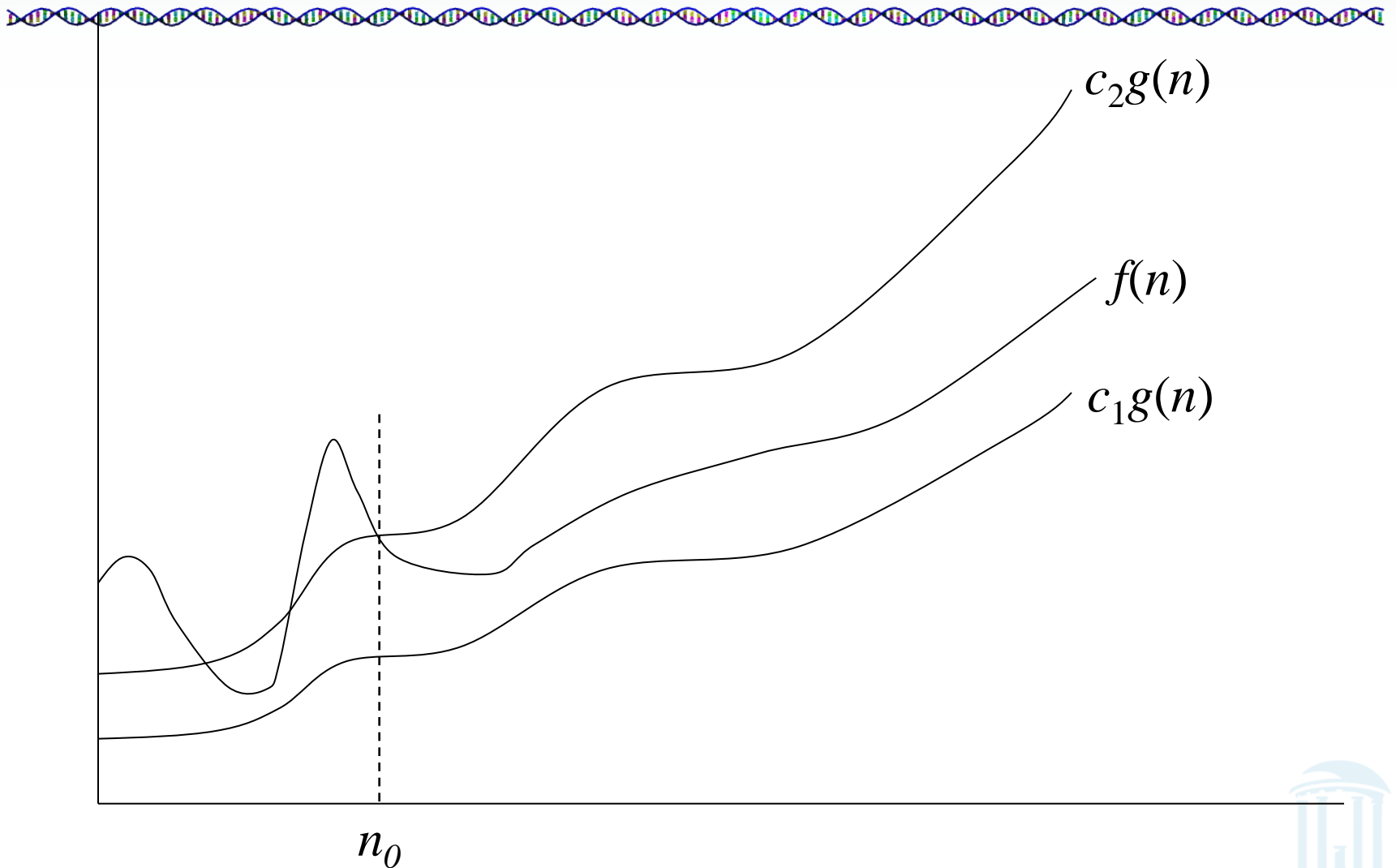
- Big- O is not a tight upper bound. In other words $n = O(n^2)$
- Θ provides a tight bound

$f(n) = \Theta(g(n))$: there exist positive constants c_1, c_2 , and n_0 such that
 $0 \leq c_1 g(n) \leq f(n) \leq c_2 g(n)$ for all $n \geq n_0$

- $n = O(n^2) \neq \Theta(n^2)$
- $200n^2 = O(n^2) = \Theta(n^2)$
- $n^{2.5} \neq O(n^2) \neq \Theta(n^2)$



Visualization of $\Theta(g(n))$



Some Other Asymptotic Functions



- Little o – A **non-tight** asymptotic upper bound

- $n = o(n^2)$, $n = O(n^2)$
- $3n^2 \neq o(n^2)$, $3n^2 = O(n^2)$

The difference between “big-O” and “little-o” is subtle. For $f(n) = O(g(n))$ the bound $0 \leq f(n) \leq c g(n)$, $n > n_0$ holds for *any* c . For $f(n) = o(g(n))$ the bound $0 \leq f(n) < c g(n)$, $n > n_0$ holds for *all* c .

- Ω – A **lower** bound

$f(n) = \Omega(g(n))$: there exist positive constants c and n_0 such that
$$f(n) \geq c g(n) \text{ for all } n \geq n_0$$

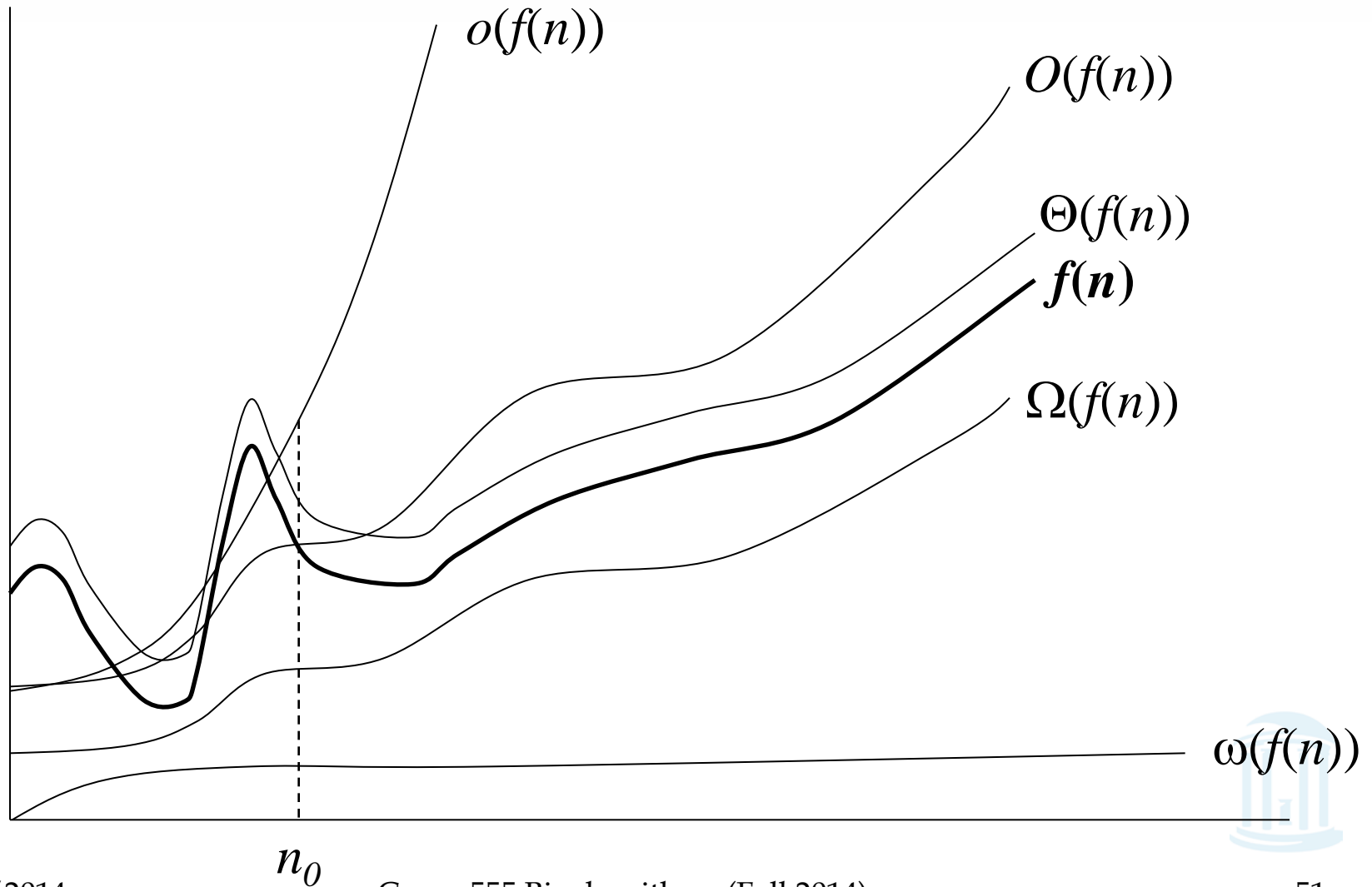
- $n^2 = \Omega(n)$

- ω – A **non-tight** asymptotic lower bound

- $f(n) = \Theta(n) \Leftrightarrow f(n) = O(n)$ **and** $f(n) = \Omega(n)$



Visualization of Asymptotic Growth



Analogy to Arithmetic Operators



$$f(n) = O(g(n)) \quad \approx \quad f \leq g$$

$$f(n) = \Omega(g(n)) \quad \approx \quad f \geq g$$

$$f(n) = \Theta(g(n)) \quad \approx \quad f = g$$

$$f(n) = o(g(n)) \quad \approx \quad f < g$$

$$f(n) = \omega(g(n)) \quad \approx \quad f > g$$



Measures of complexity



- Best case
 - **Super-fast in some limited situation is not very valuable information**
- Worst case
 - **Good upper-bound on behavior**
 - **Never gets worse than this**
- Average case
 - **Averaged over all possible inputs**
 - **Most useful information about overall performance**
 - **Can be hard to compute precisely**



Complexity



- Space Complexity $S_p(n)$: how much memory an algorithm needs (as a function of n)
- Space complexity $S_p(n)$ is not necessarily the same as the time complexity $T(n)$
 - $T(n) \geq S_p(n)$



Next Time



- Our first “bio” algorithm
- Read book 4.1 – 4.3

