



Lesson 6 Objectives:

To gain an understanding of:

1. What **dynamic programming** (DP) is and how it works
2. How to **identify** DP problems
3. How to use of **memoization** and **tabulation** to solve DP problems
4. How to analyse **time complexities** of recursive and DP algorithms

Dynamic Programming

Dynamic Programming

- **Dynamic Programming (DP)** is an optimisation technique where we take the answers of sub problems, and use that to help solve the larger problem.
- This may sound reminiscent of **RECURSION** and this is because DP is essentially a **optimisation over plain recursion**

Dynamic Programming

- Plainly speaking, DP is useful in allowing us to make algorithms, **where the same computations are done over and over again**, more efficient through the use of **caching**

Dynamic Programming

- Plainly speaking, DP is useful in allowing us to make algorithms, **where the same computations are done over and over again**, more efficient through the use of **caching**
- This can be done through two methods:
 1. **Memoization**: Top down approach
 2. **Tabulation**: Bottom up approach

Introduction to DP & Memoization

Problem #1: Fibonacci

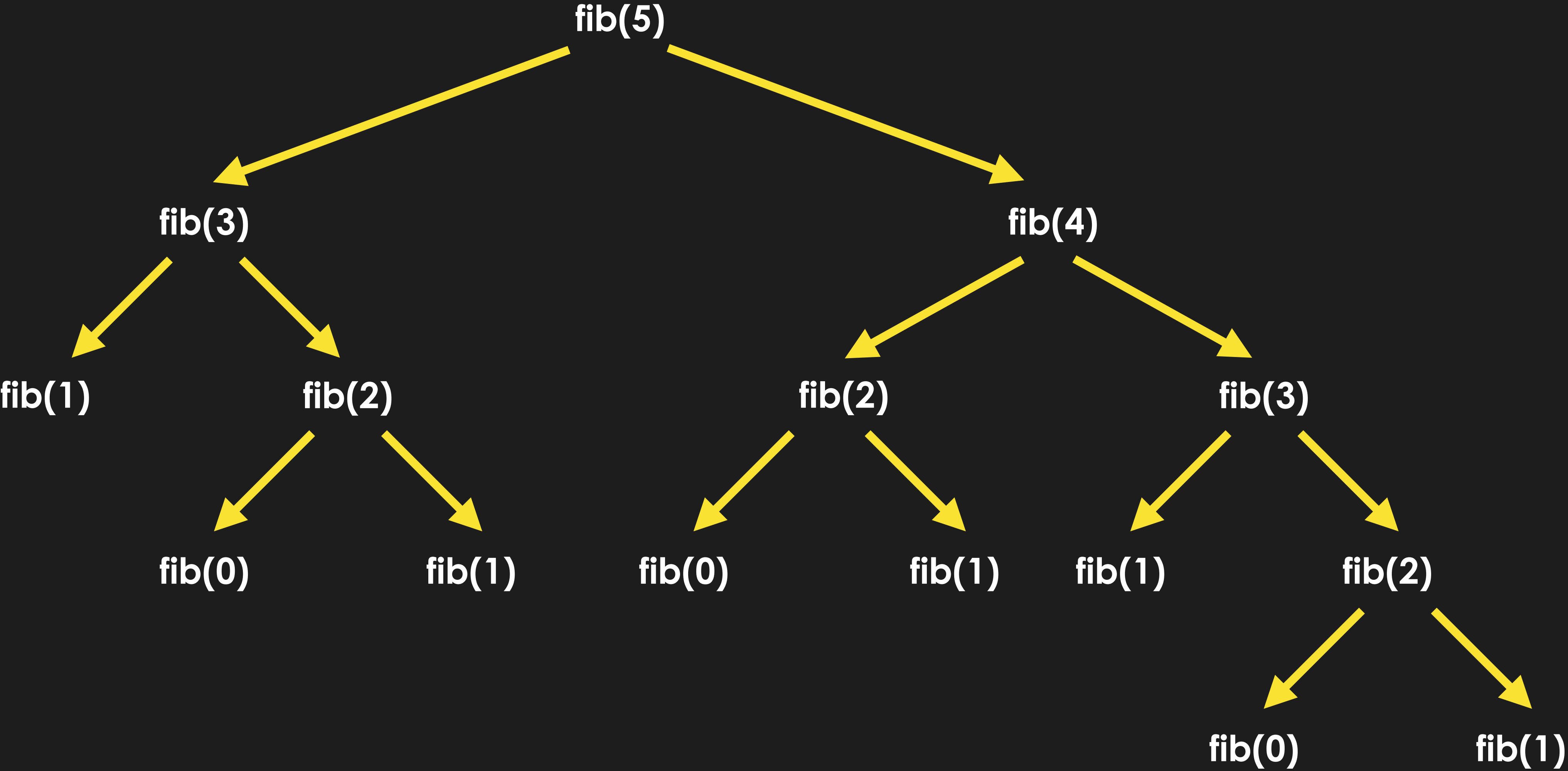
Fib: Calculate the **fibonacci number** given an input **N**

n	0	1	2	3	4	5	6
fib(n)	1	1	2	3	5	8	13

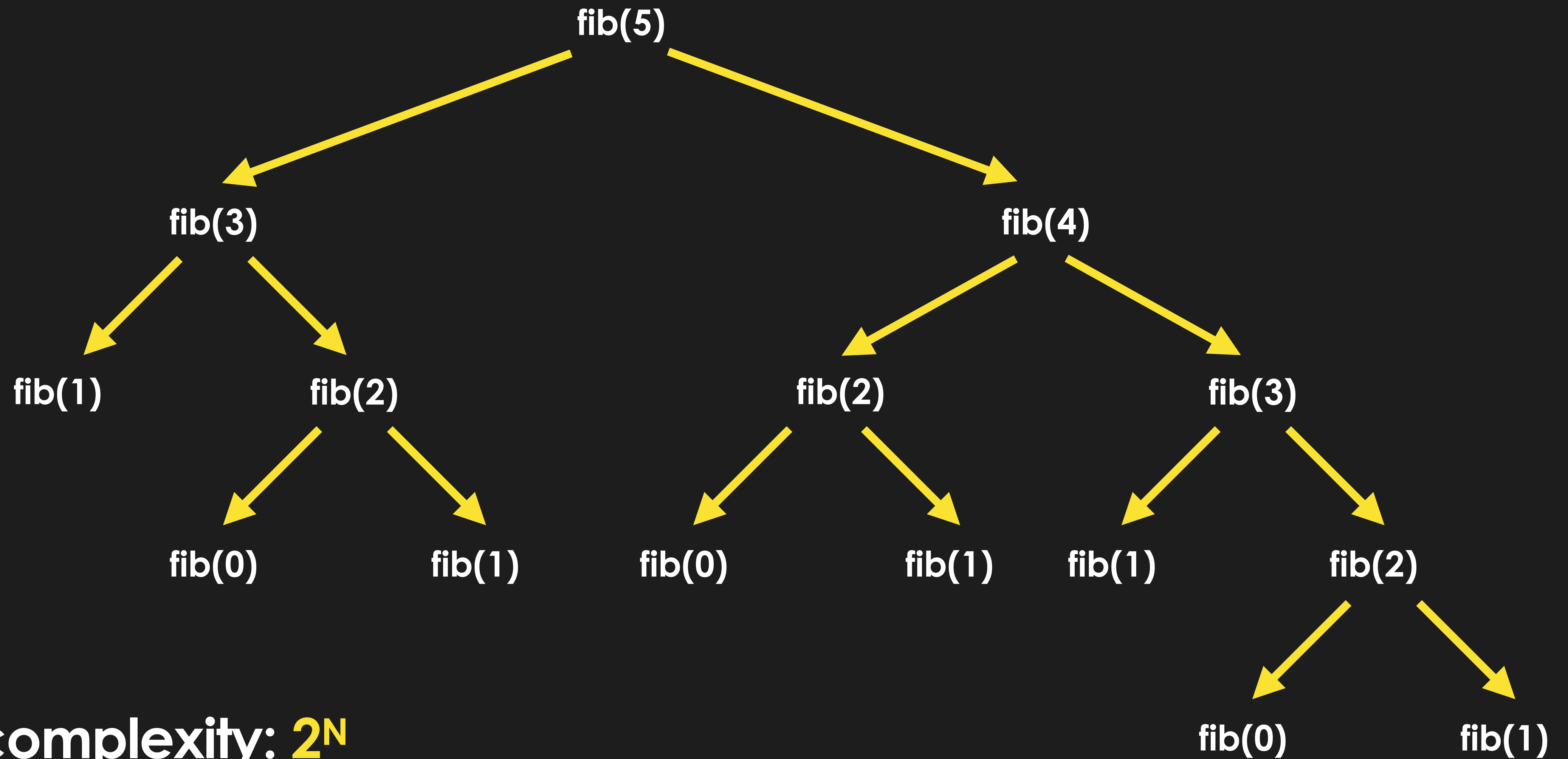
fib

```
def fib(n):  
    if n == 0 or n == 1:  
        return 1  
    else:  
        return fib(n - 1) + fib(n - 2)
```

fib

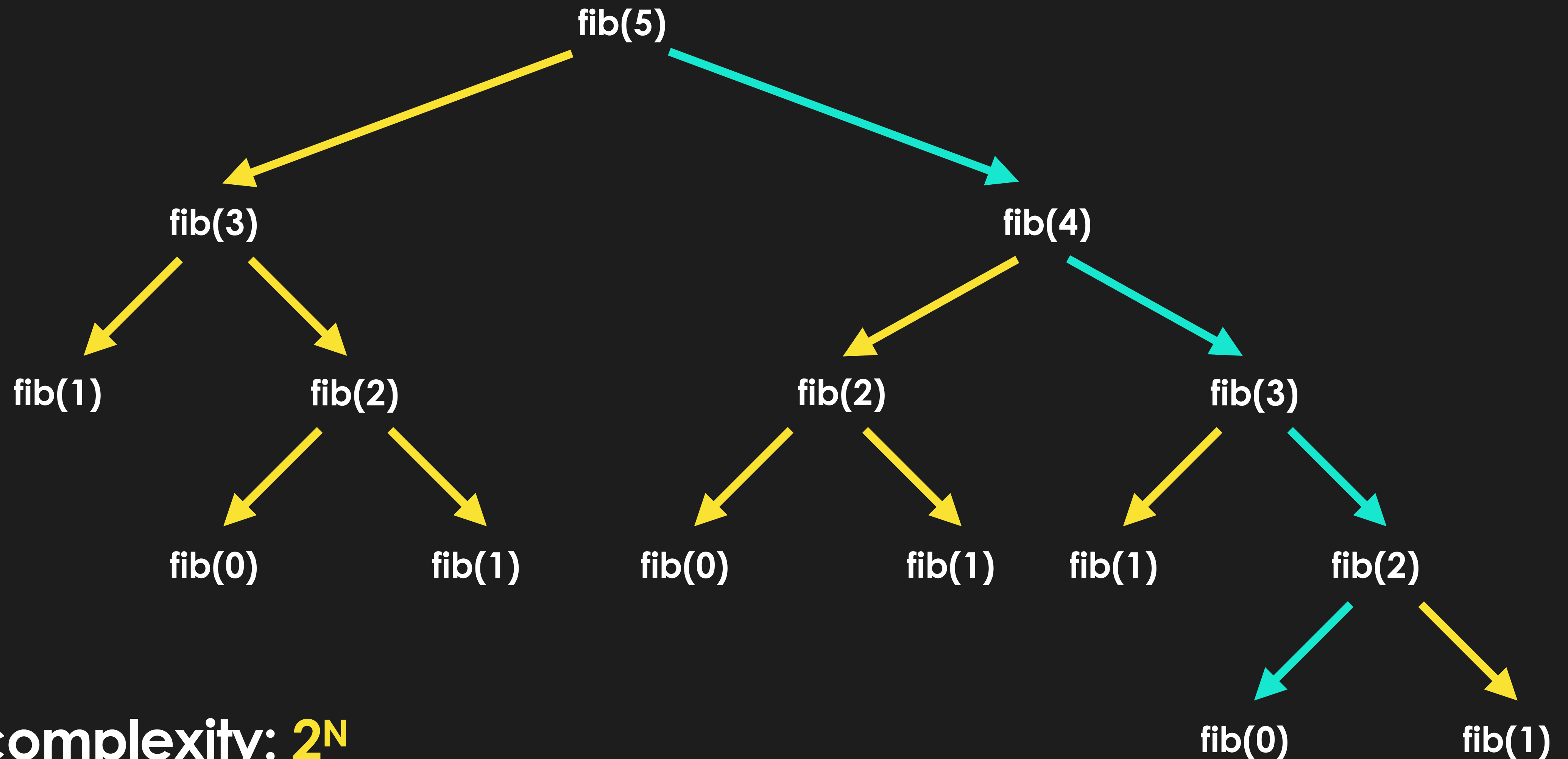


fib



time complexity: 2^N

fib

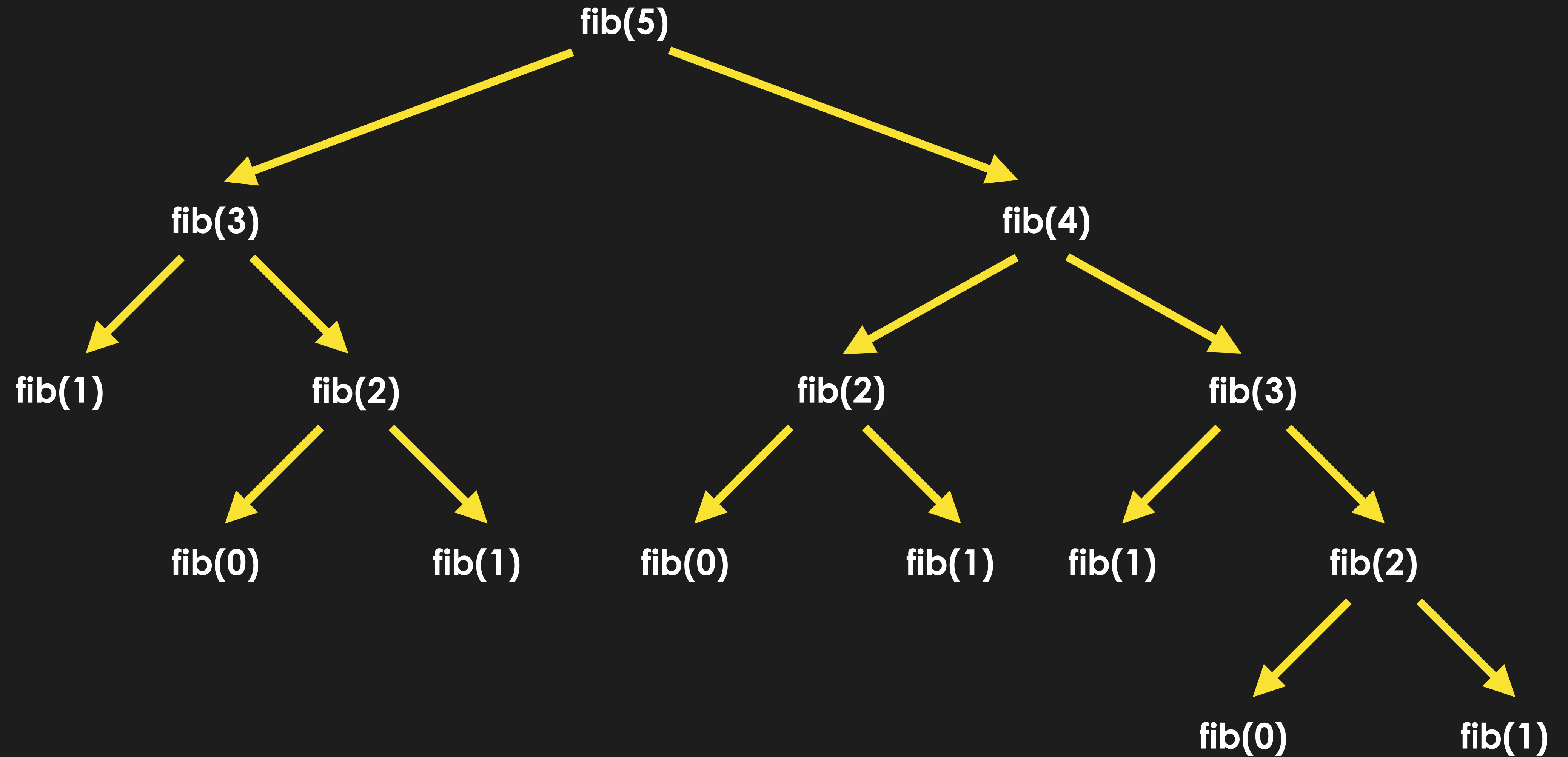


time complexity: 2^N

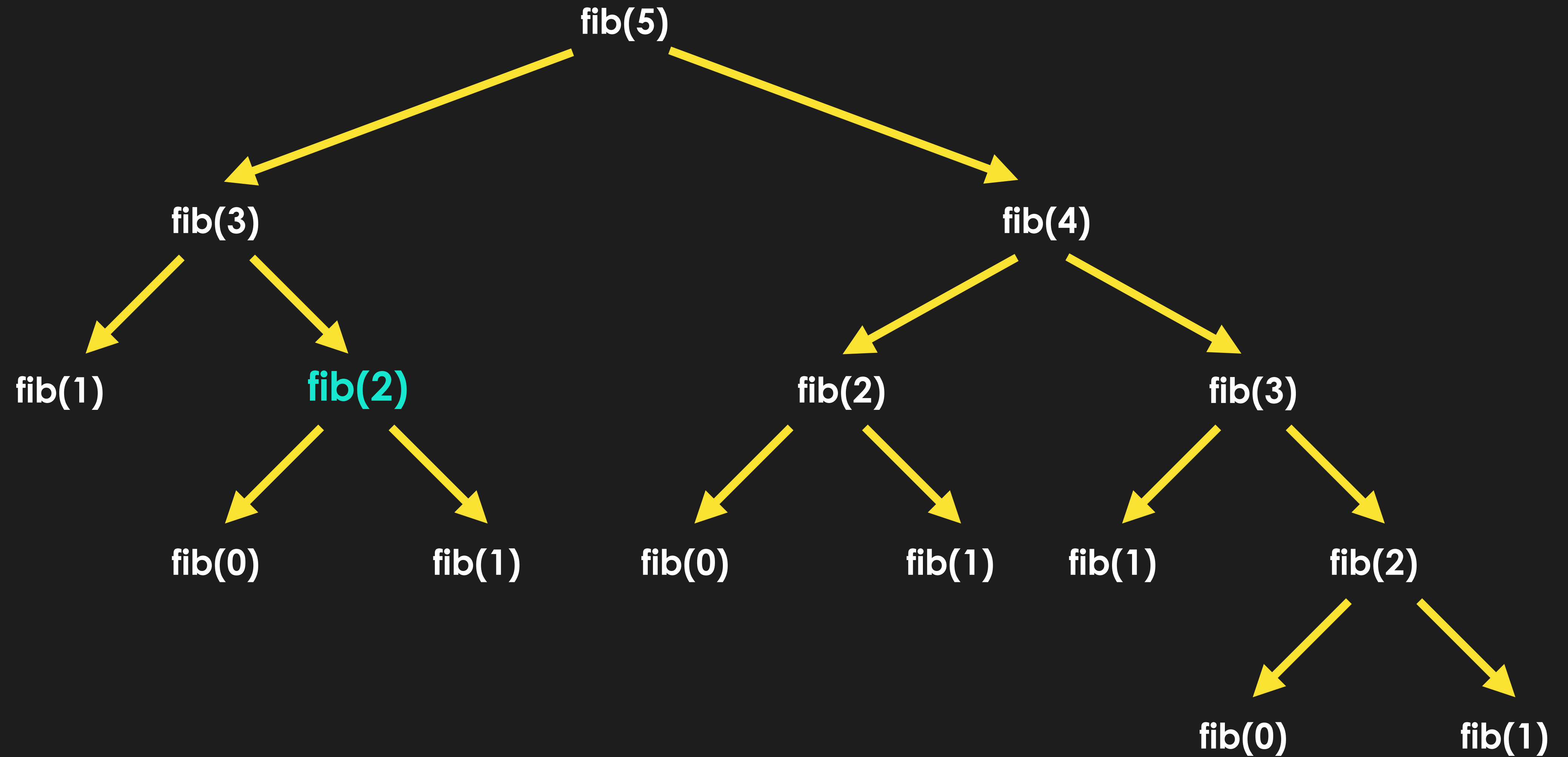
space complexity: N

(at any time, the number of recursive calls on the stack is N)

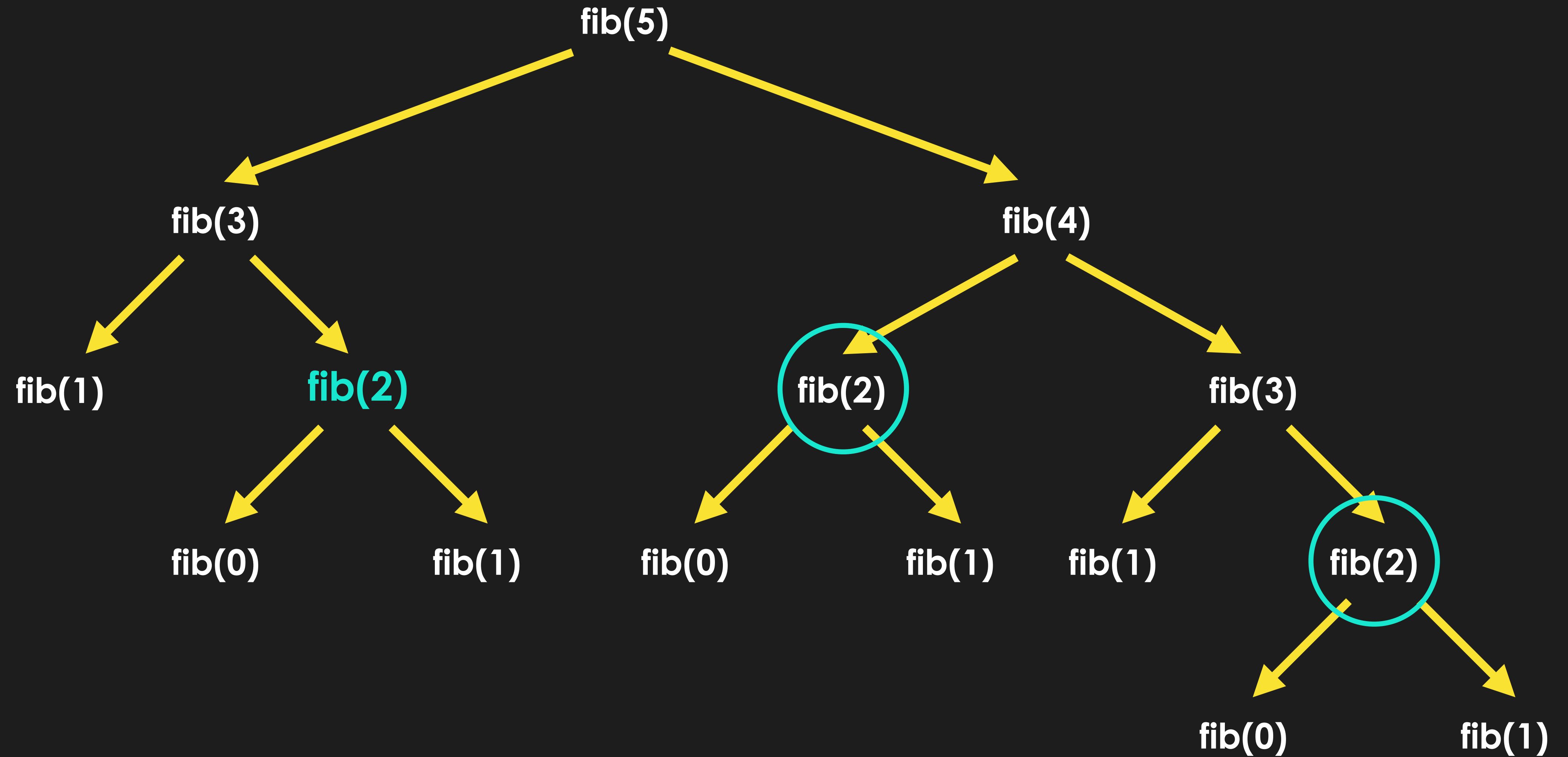
Notice how we are repeating certain computations



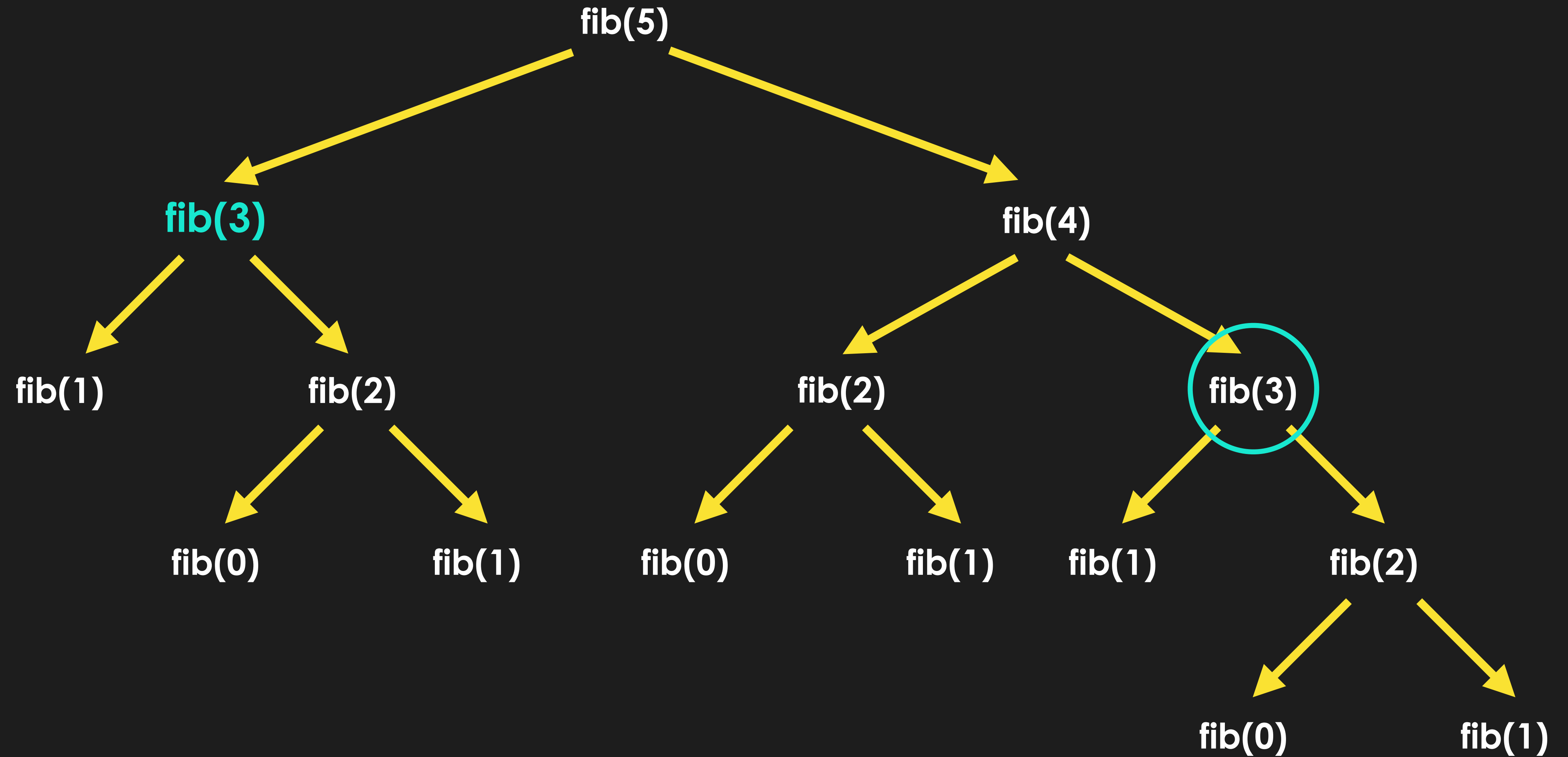
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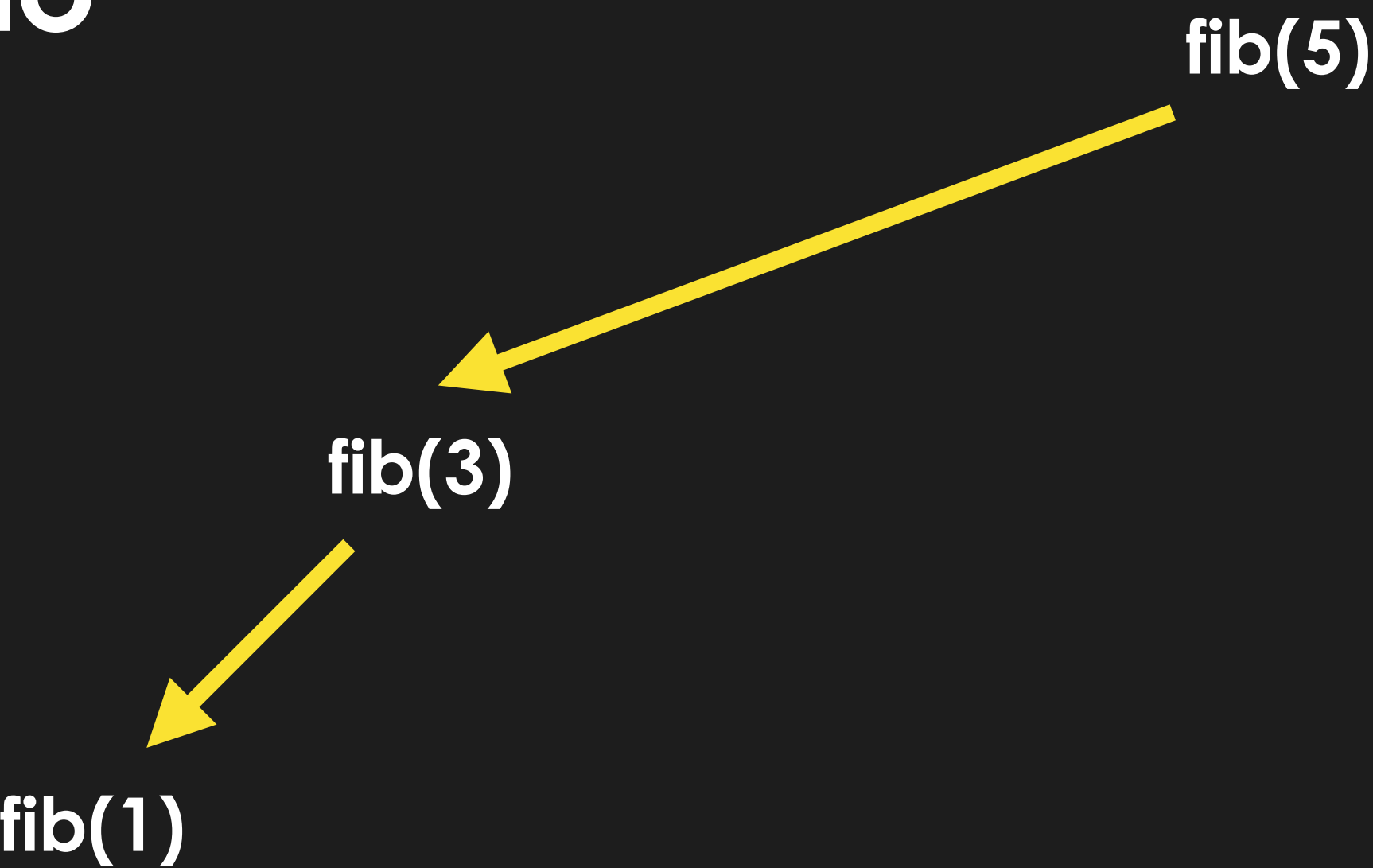


Notice how we are repeating certain computations



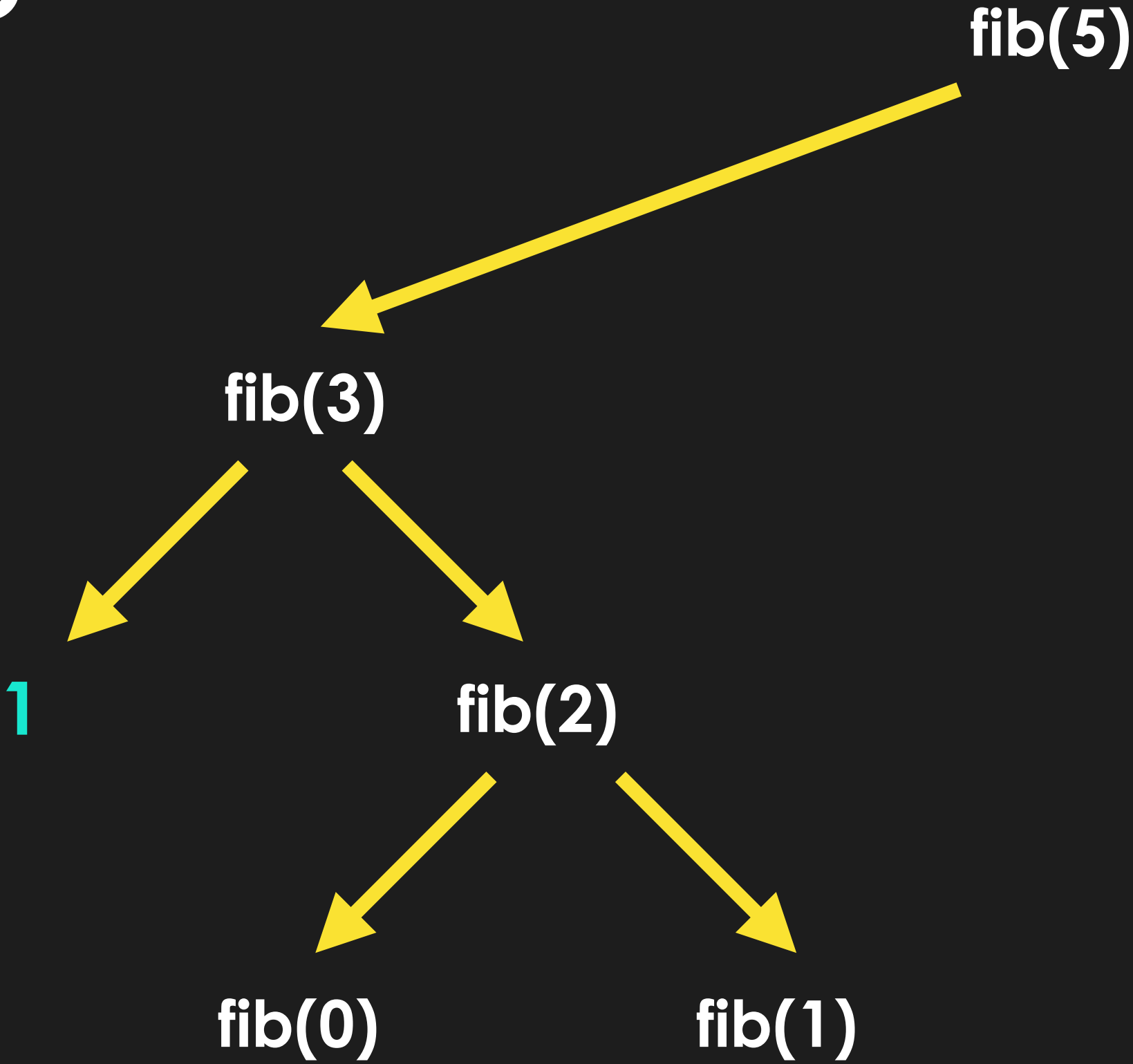
How to avoid recomputation? Memoization!

Fib Memo



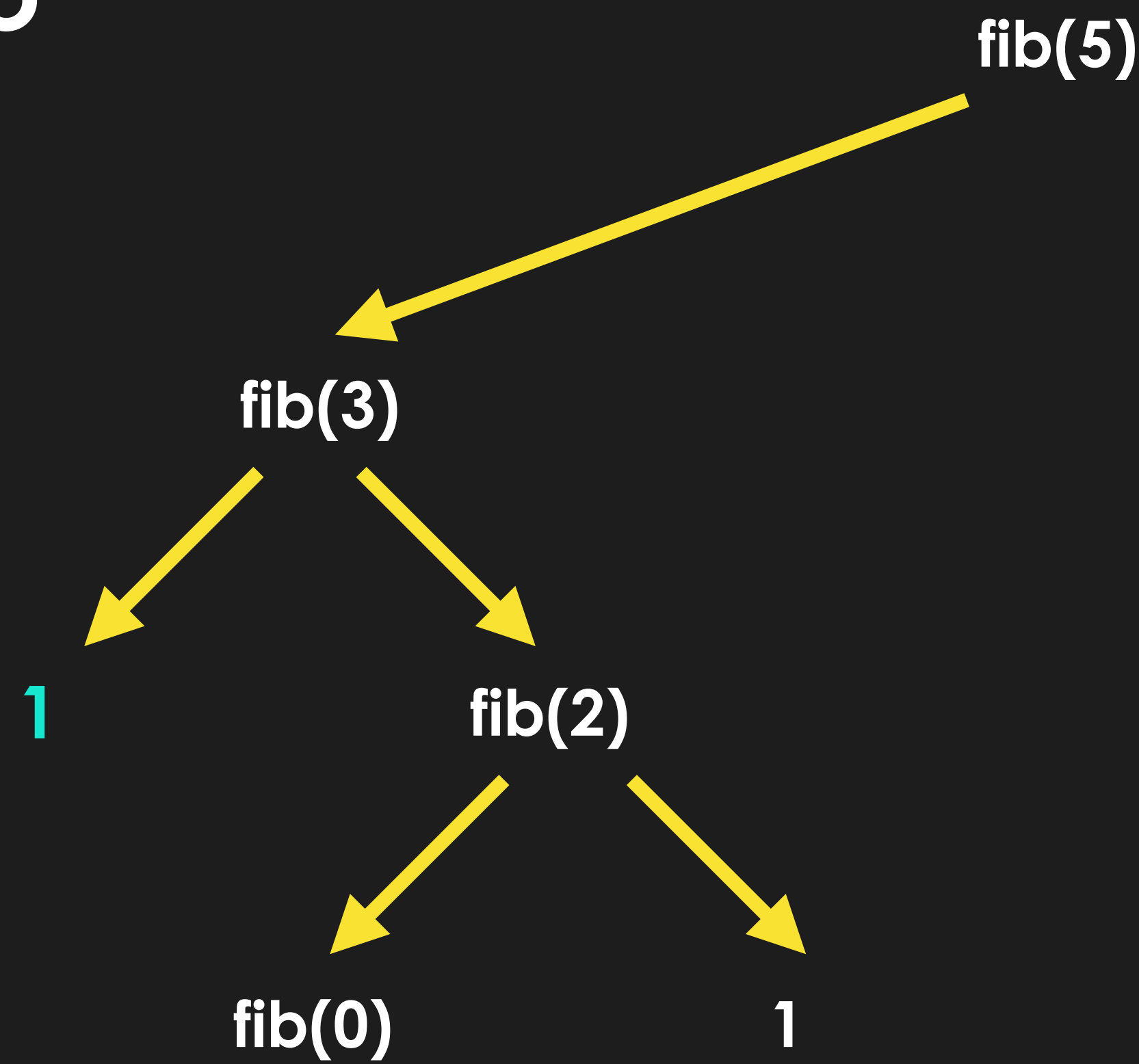
n						
memo[n]						

Fib Memo



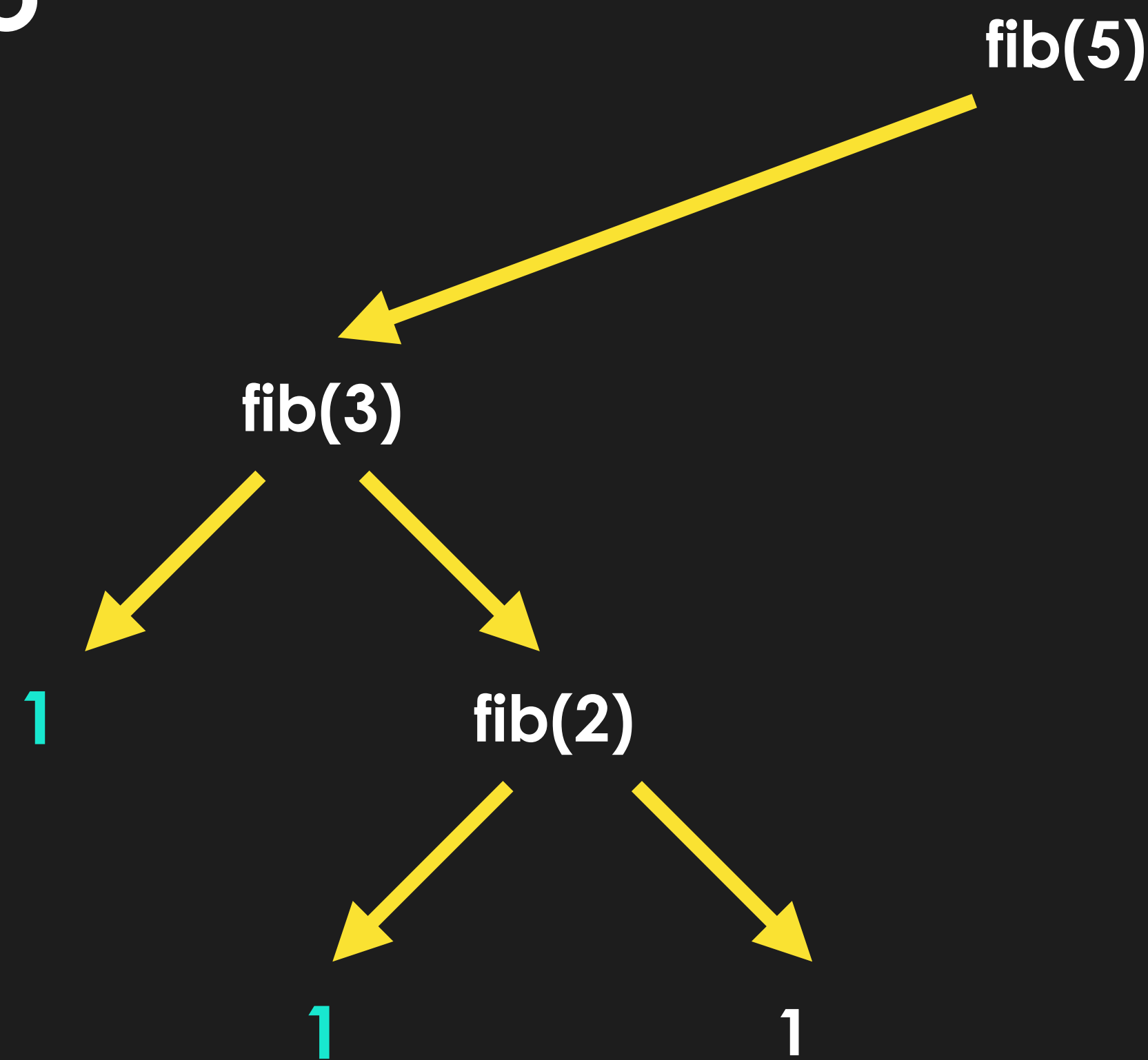
n		1				
memo[n]		1				

Fib Memo



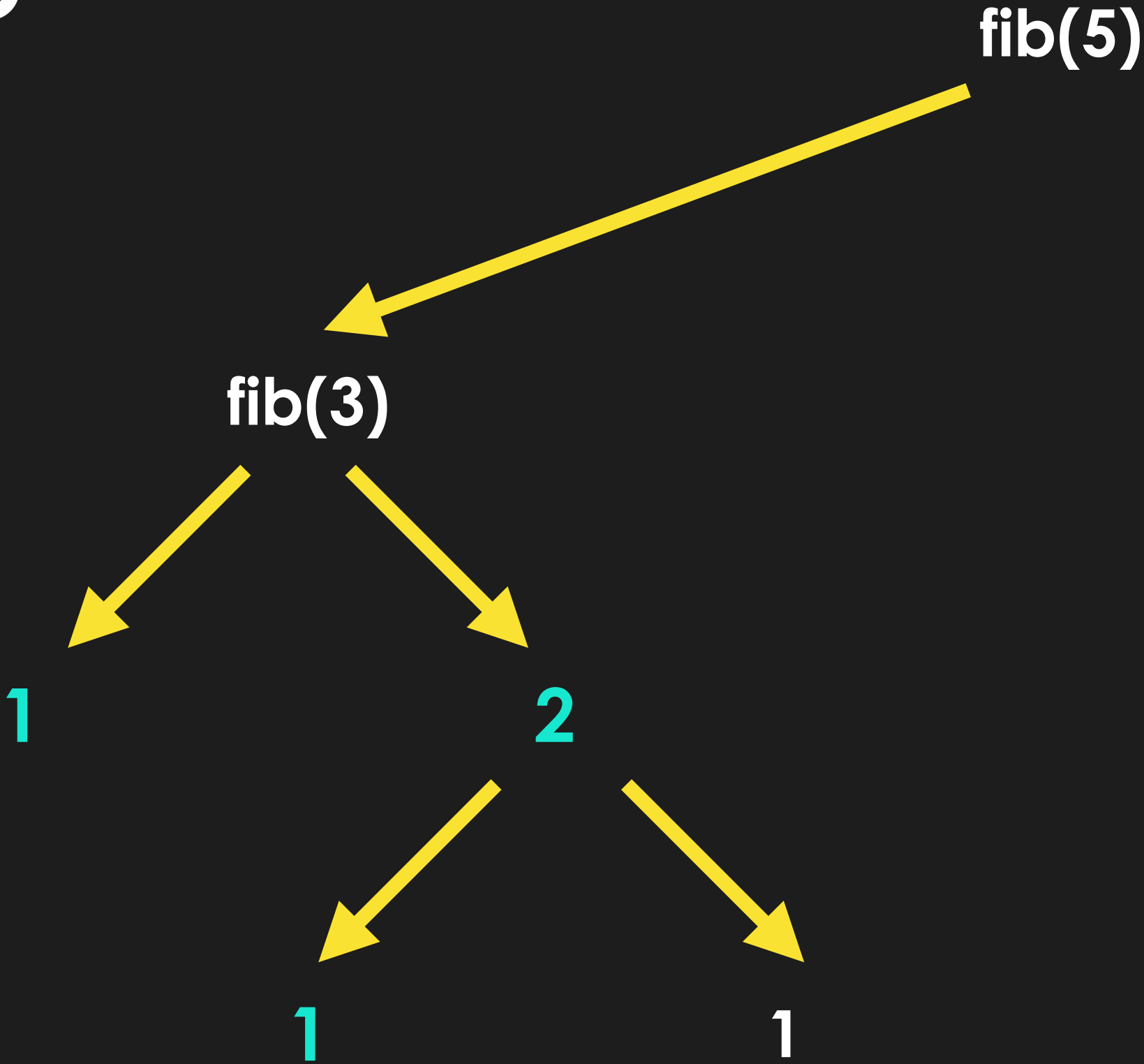
n		1				
memo[n]		1				

Fib Memo



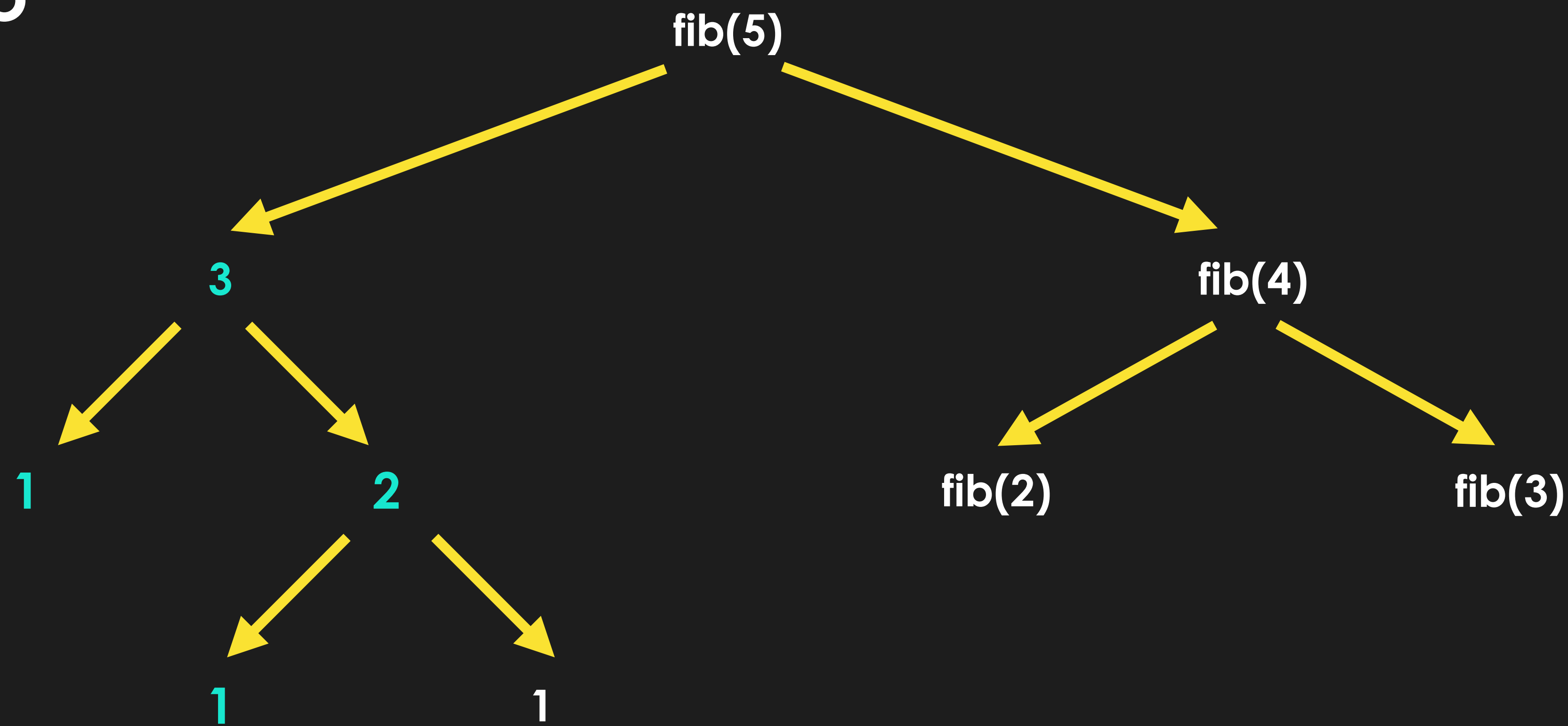
n	0	1				
memo[n]	1	1				

Fib Memo



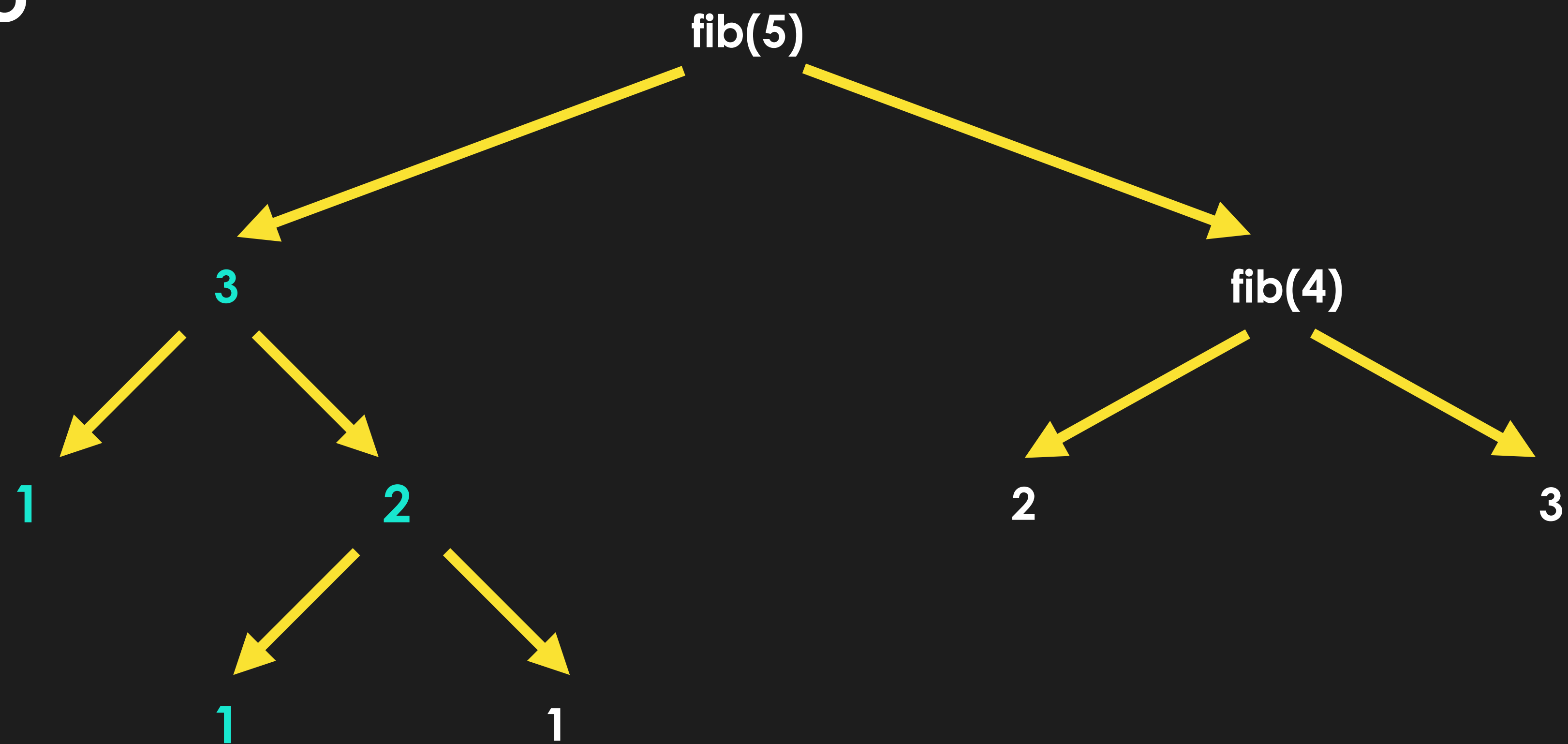
n	0	1	2			
memo[n]	1	1	2			

Fib Memo



n	0	1	2	3		
memo[n]	1	1	2	3		

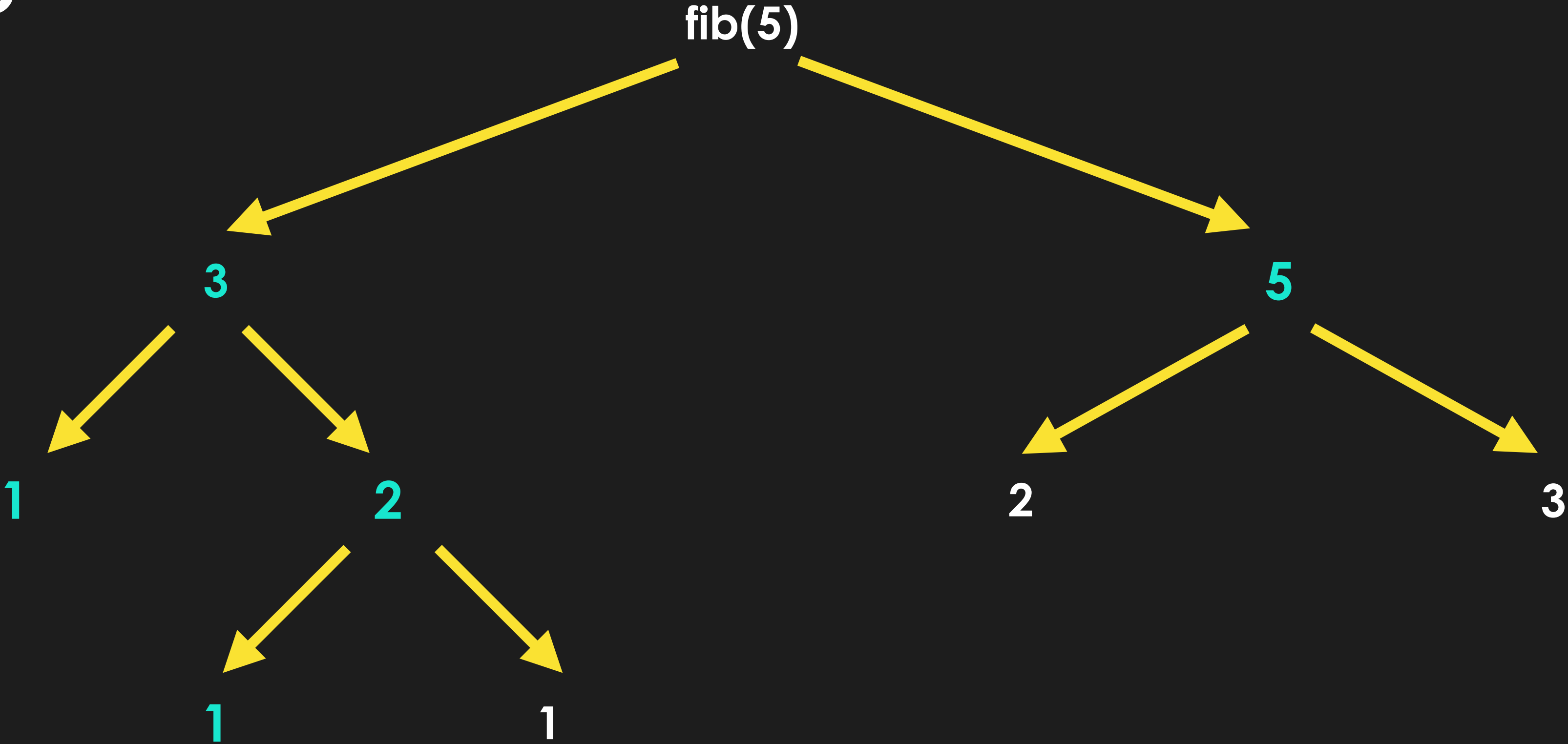
Fib Memo



n	0	1	2	3		
memo[n]	1	1	2	3		

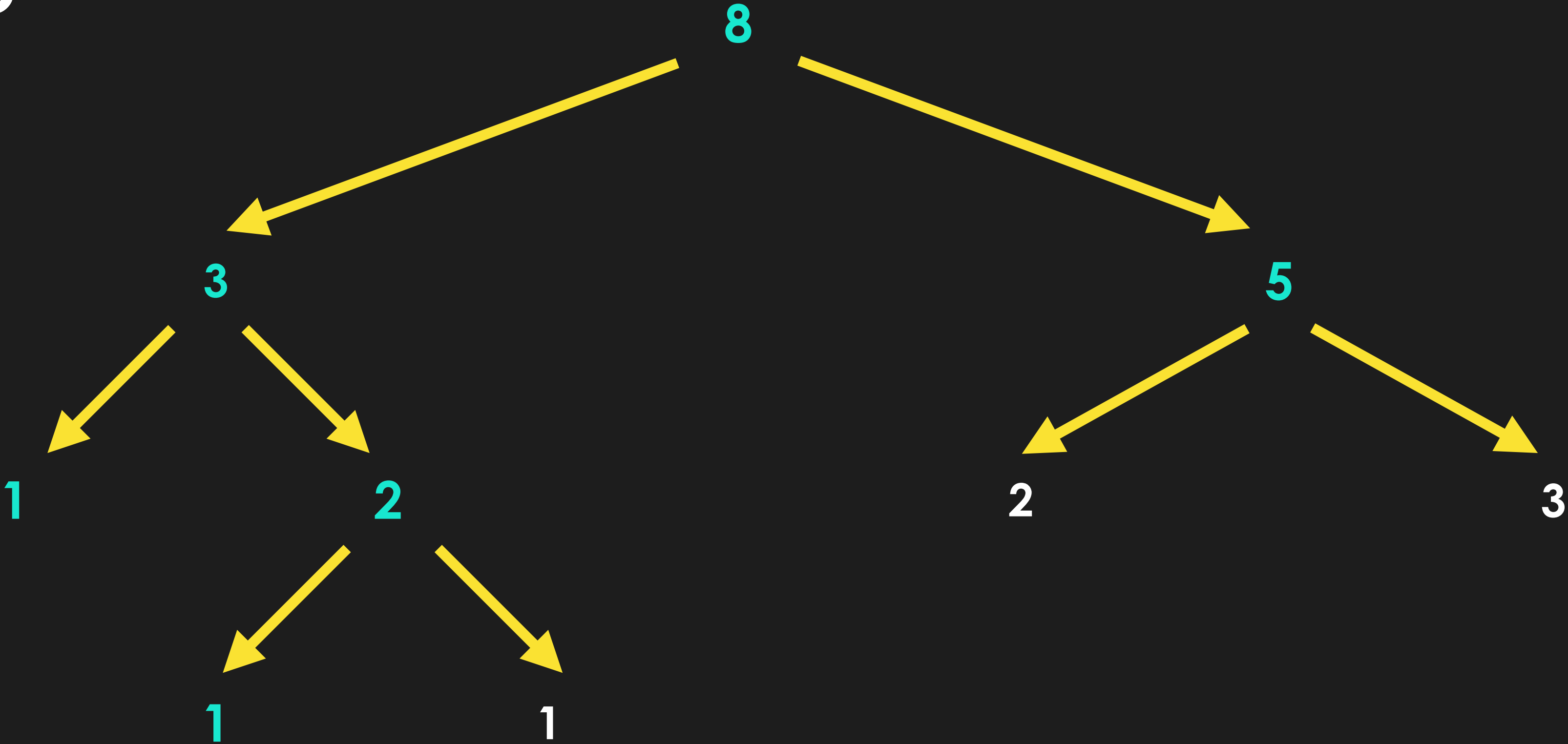
Already in table!

Fib Memo



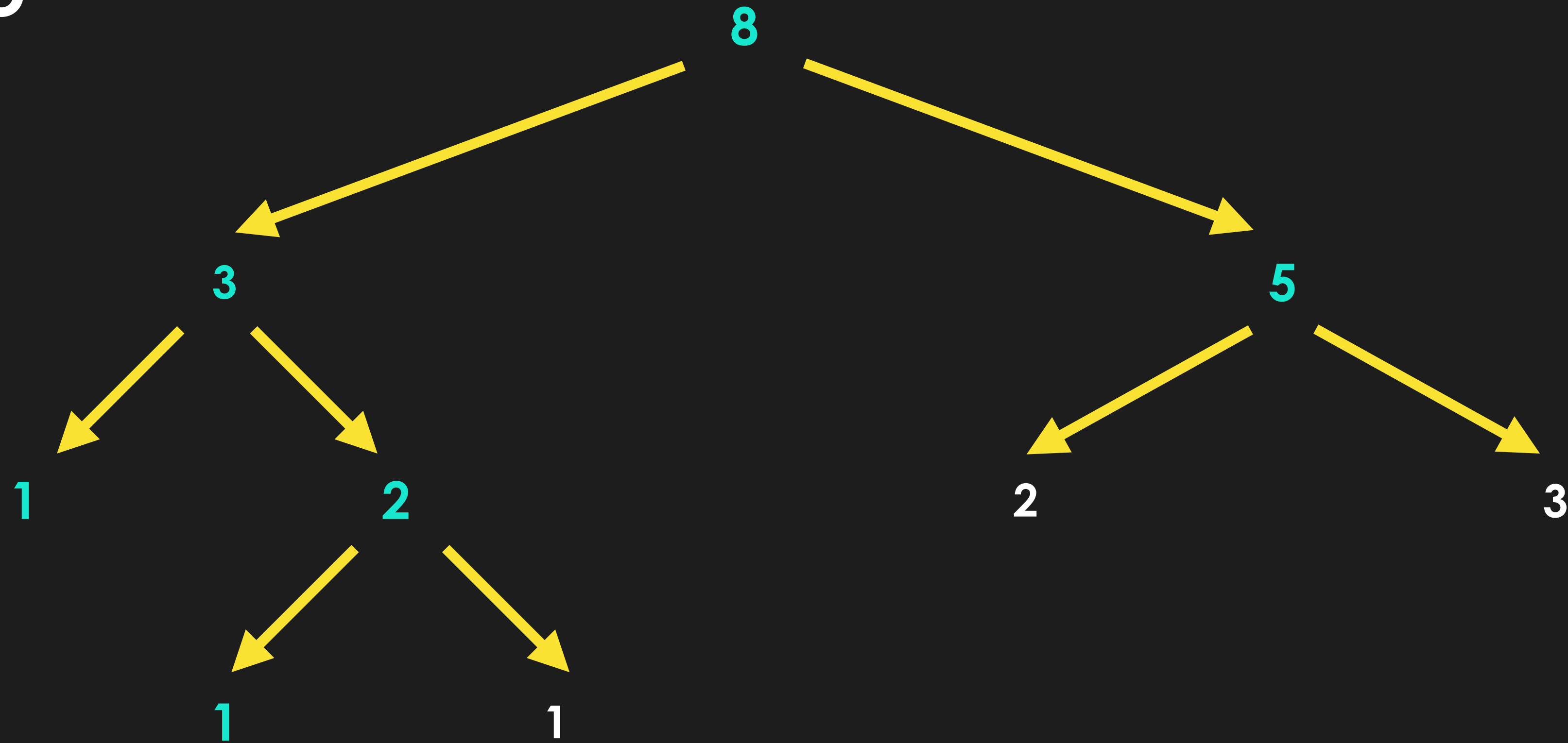
n	0	1	2	3	4	
memo[n]	1	1	2	3	5	

Fib Memo



n	0	1	2	3	4	5
memo[n]	1	1	2	3	5	8

Fib Memo



n	0	1	2	3	4	5
memo[n]	1	1	2	3	5	8

time complexity: **N**

space complexity: **N**

Fib Memo

```
memo = {}

def fibMemo(n):
    if n in memo:
        return memo[n]

    elif n == 0 or n == 1:
        return 1

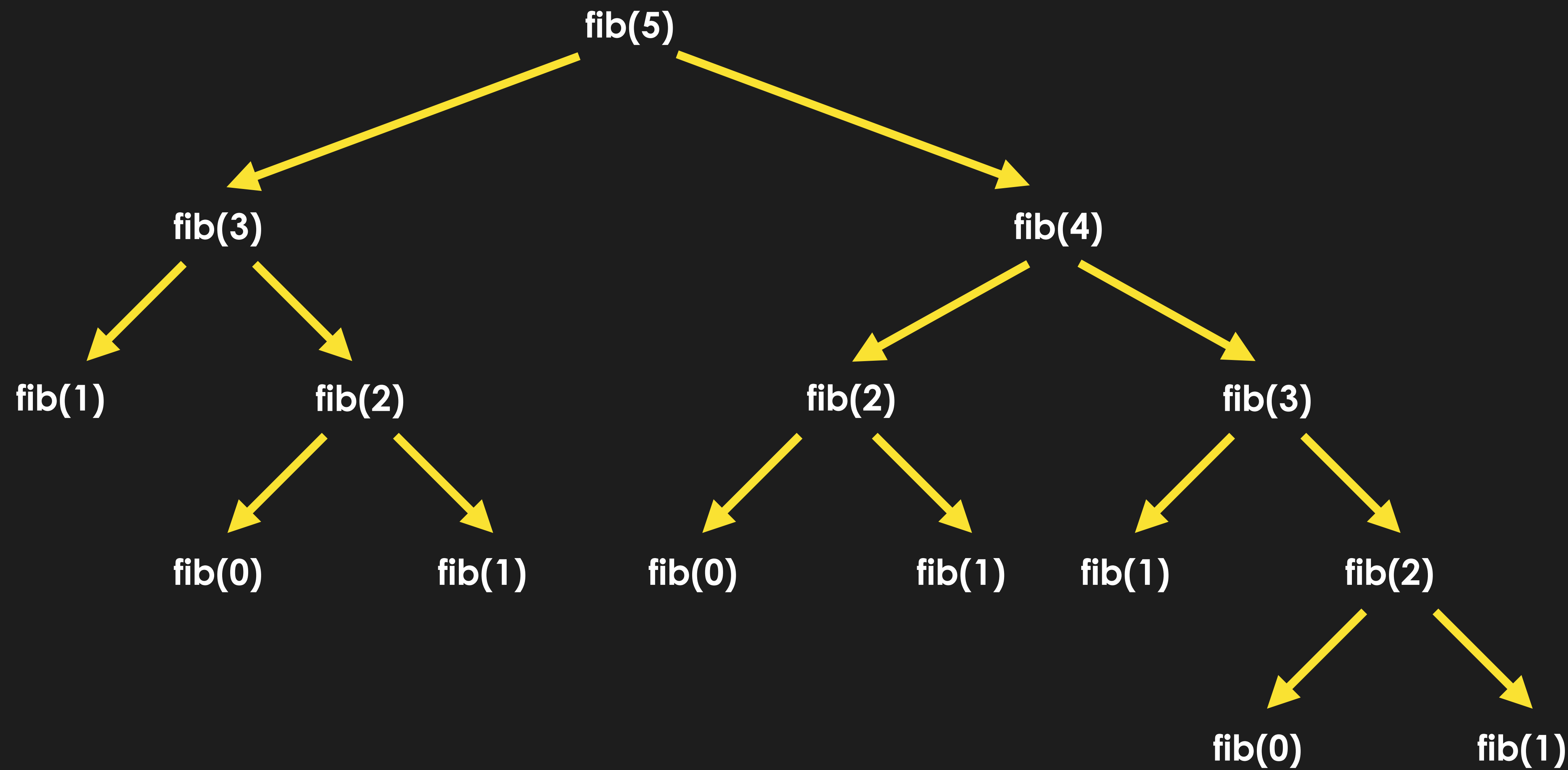
    else:
        memo[n] = fibMemo(n - 1) + fibMemo(n - 2)
        return memo[n]
```

Identifying a DP problem

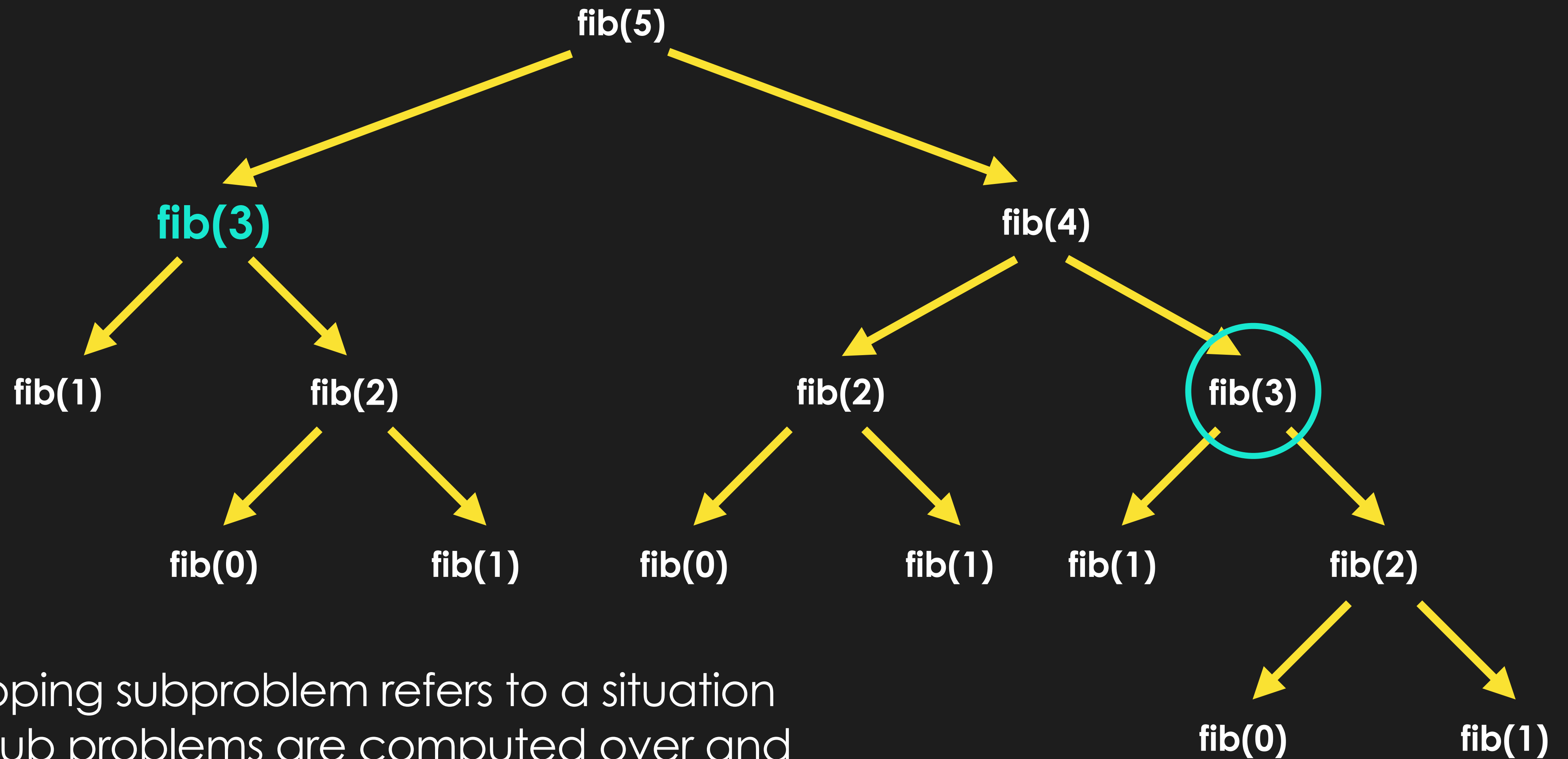
Properties of a dynamic problem

- Overlapping subproblems
- Optimal substructure

Overlapping subproblems



Overlapping subproblems



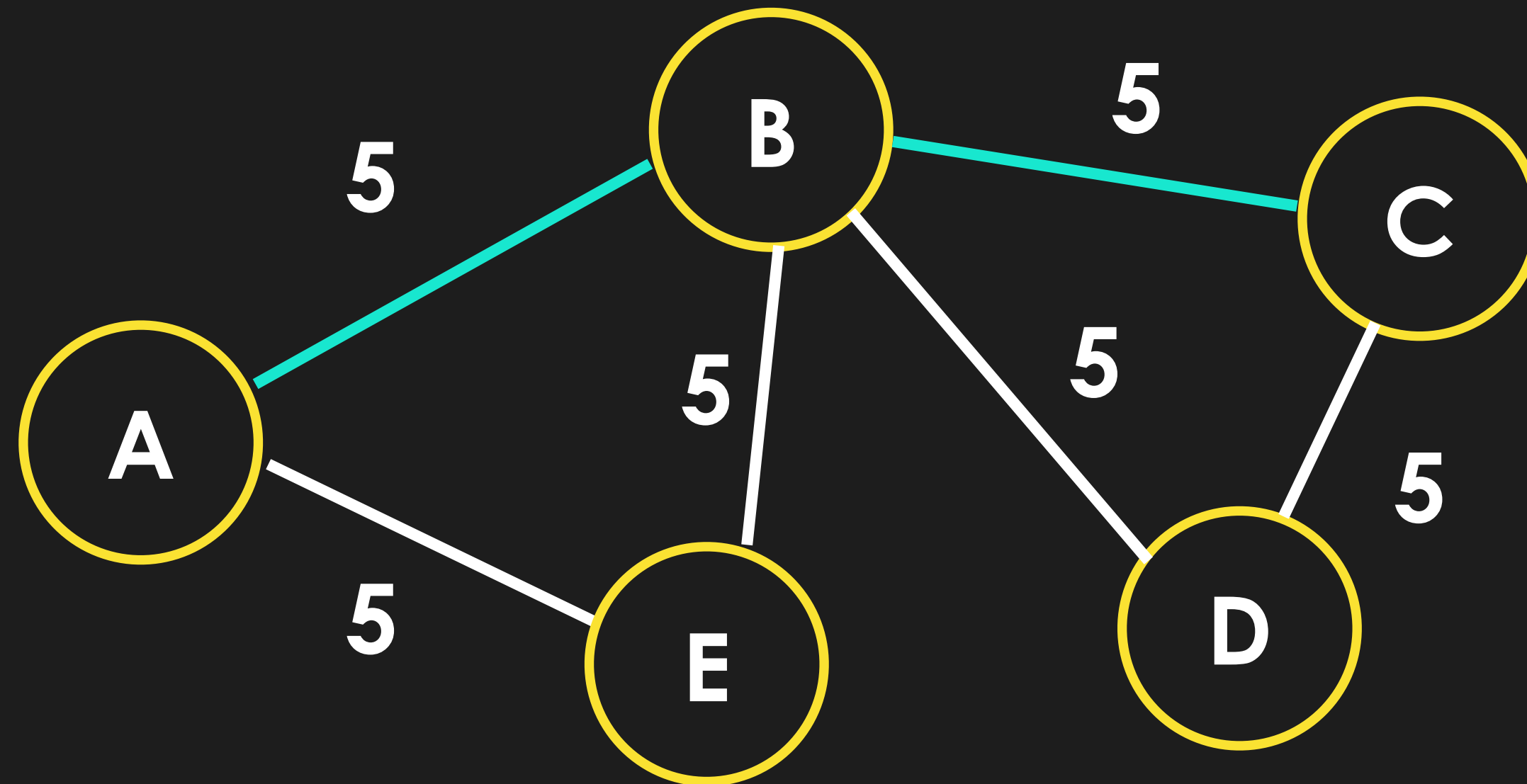
Overlapping subproblem refers to a situation where sub problems are computed over and over again

Optimal substructure is when for a **problem of size N** , the optimal solution can be derived or calculated from the **optimal solutions to some number of sub problems**

Optimal substructure in fib

- $\text{fib}(5) = \text{fib}(4) + \text{fib}(3)$
- The **optimal solution for fib(5)**, can be calculated from the **optimal solution of sub problem fib(4)** and **optimal solution of sub problem fib(3)**

Another example of optimal substructure: shortest paths



Given solutions to subproblems [$SP(A, D)$, $SP(B, C)$, $SP(A, D)$, $SP(D, C)$], the larger problem $SP(A, C)$ can be found

Brain Teaser: How do you think greedy algorithms and optimal substructures relate?

Back to properties of a dynamic problem

- **Overlapping subproblems**

If a problem has overlapping subproblems, then recursive solutions to subproblems can be stored in a cache (memo object) and thus recomputation can be avoided

- **Optimal substructure:**

If a problem has an optimal substructure, then it can be recursively broken down into sub problems and built back up using the subproblem solutions

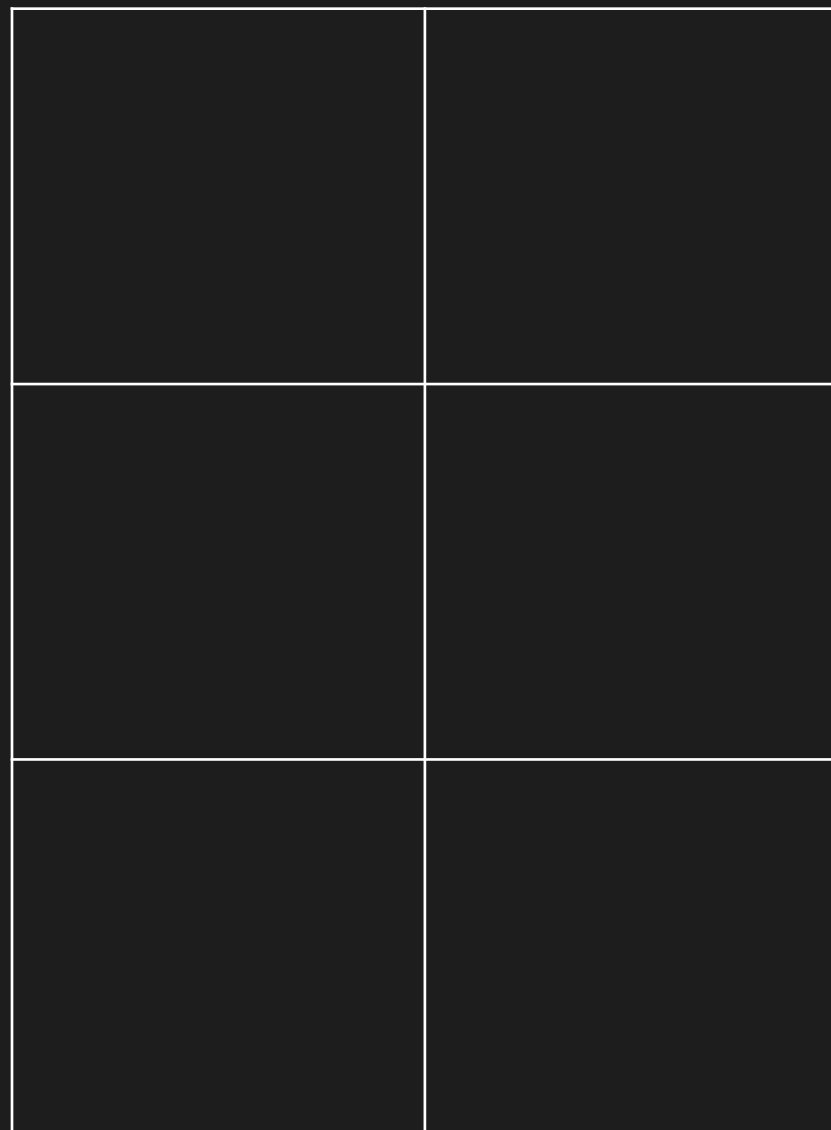
This is the rationale behind memoization and recursion to solve DP problems!

DP Problem #2: Unique Paths

DP Problem #2: Unique Paths

Given an $m \times n$ grid, assuming you can only move **right & down**, calculate the total number of unique paths to get from **top left to bottom right**

Example: 3 x 2 grid

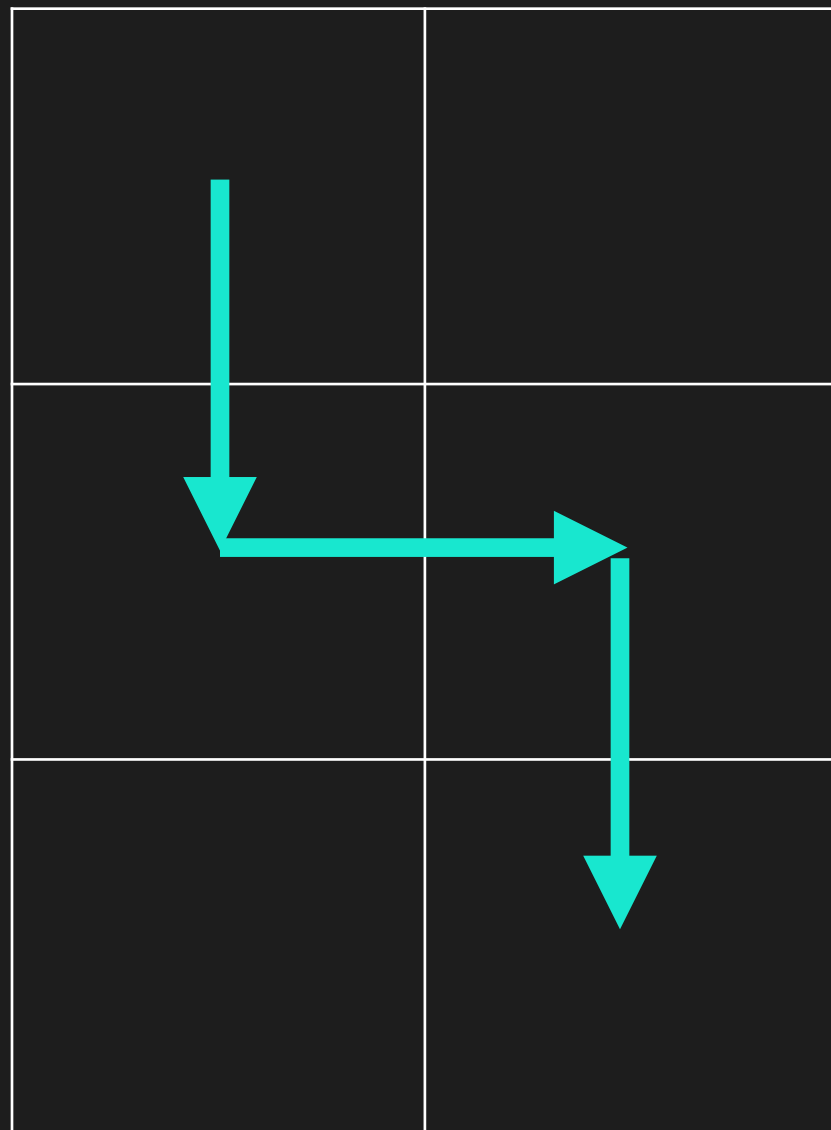


UniquePaths(3, 2) =>

DP Problem #2: Unique Paths

Given an $m \times n$ grid, assuming you can only move **right & down**, calculate the total number of unique paths to get from **top left to bottom right**

Example: 3 x 2 grid

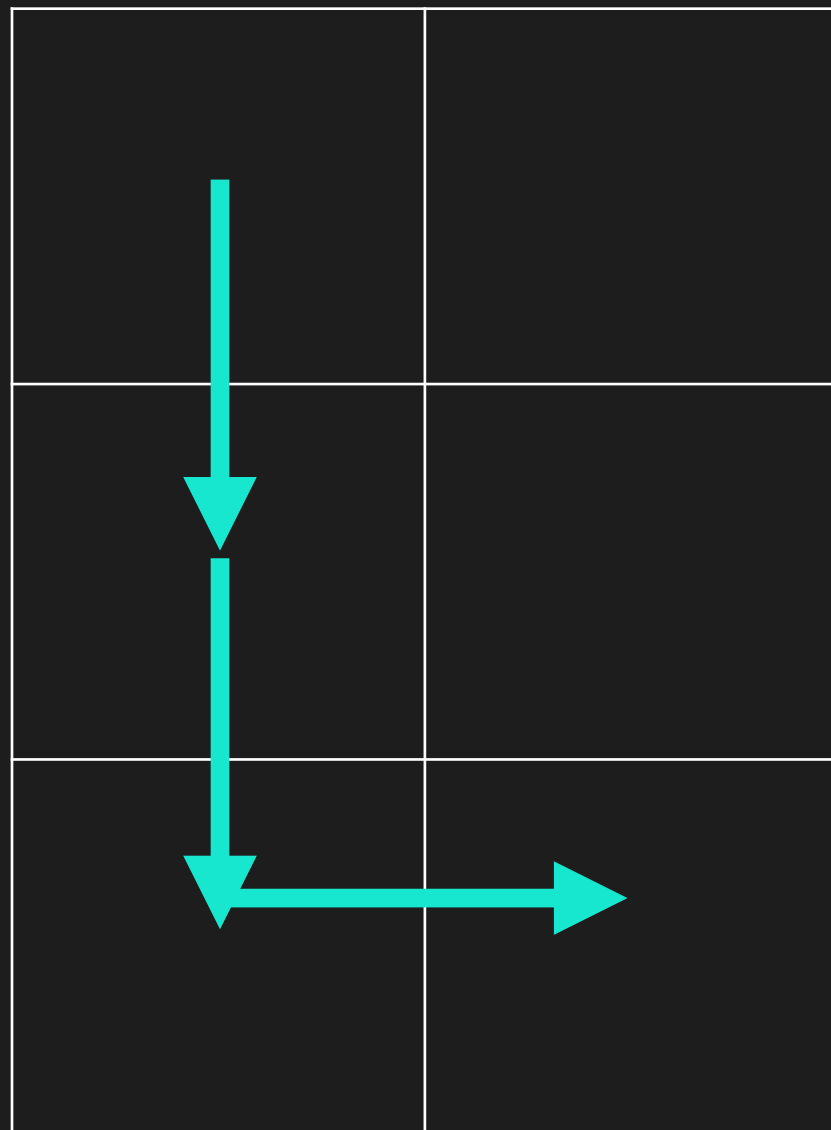


UniquePaths(3, 2) => 1

DP Problem #2: Unique Paths

Given an $m \times n$ grid, assuming you can only move **right & down**, calculate the total number of unique paths to get from **top left to bottom right**

Example: 3 x 2 grid

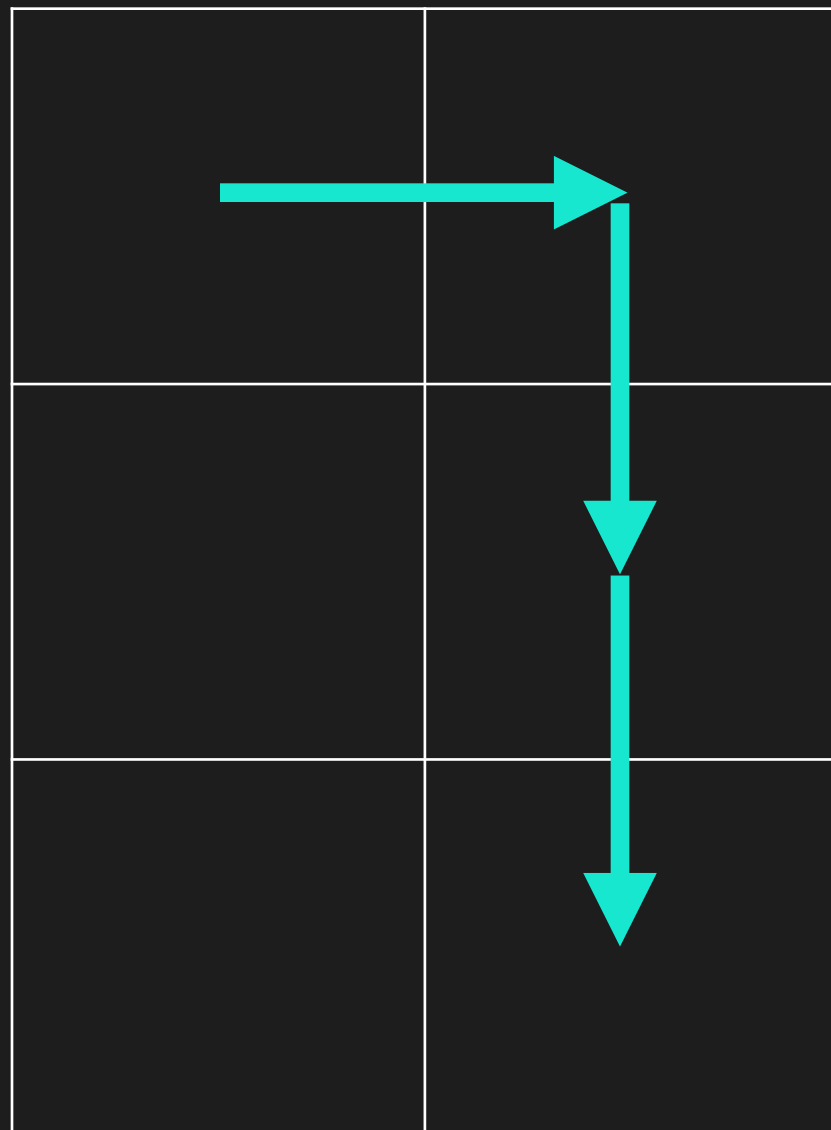


UniquePaths(3, 2) => 2

DP Problem #2: Unique Paths

Given an $m \times n$ grid, assuming you can only move **right & down**, calculate the total number of unique paths to get from **top left to bottom right**

Example: 3 x 2 grid



UniquePaths(3, 2) => 3

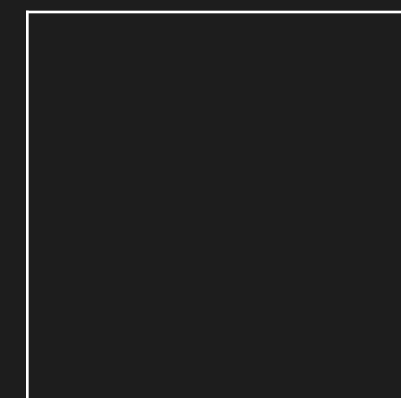
DP Problem #2: Unique Paths

Given an $m \times n$ grid, assuming you can only move **right & down**, calculate the total number of unique paths to get from **top left to bottom right**

Defining the problem: smallest problem size

If either m or n is 0:
uniquePaths is 0

For a 1×1 , 1×2 , 2×1 board:
uniquePaths is 1



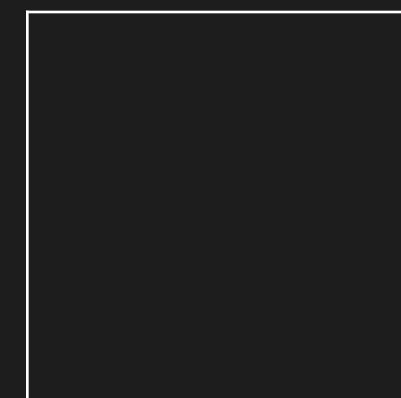
DP Problem #2: Unique Paths

Given an $m \times n$ grid, assuming you can only move **right & down**, calculate the total number of unique paths to get from **top left to bottom right**

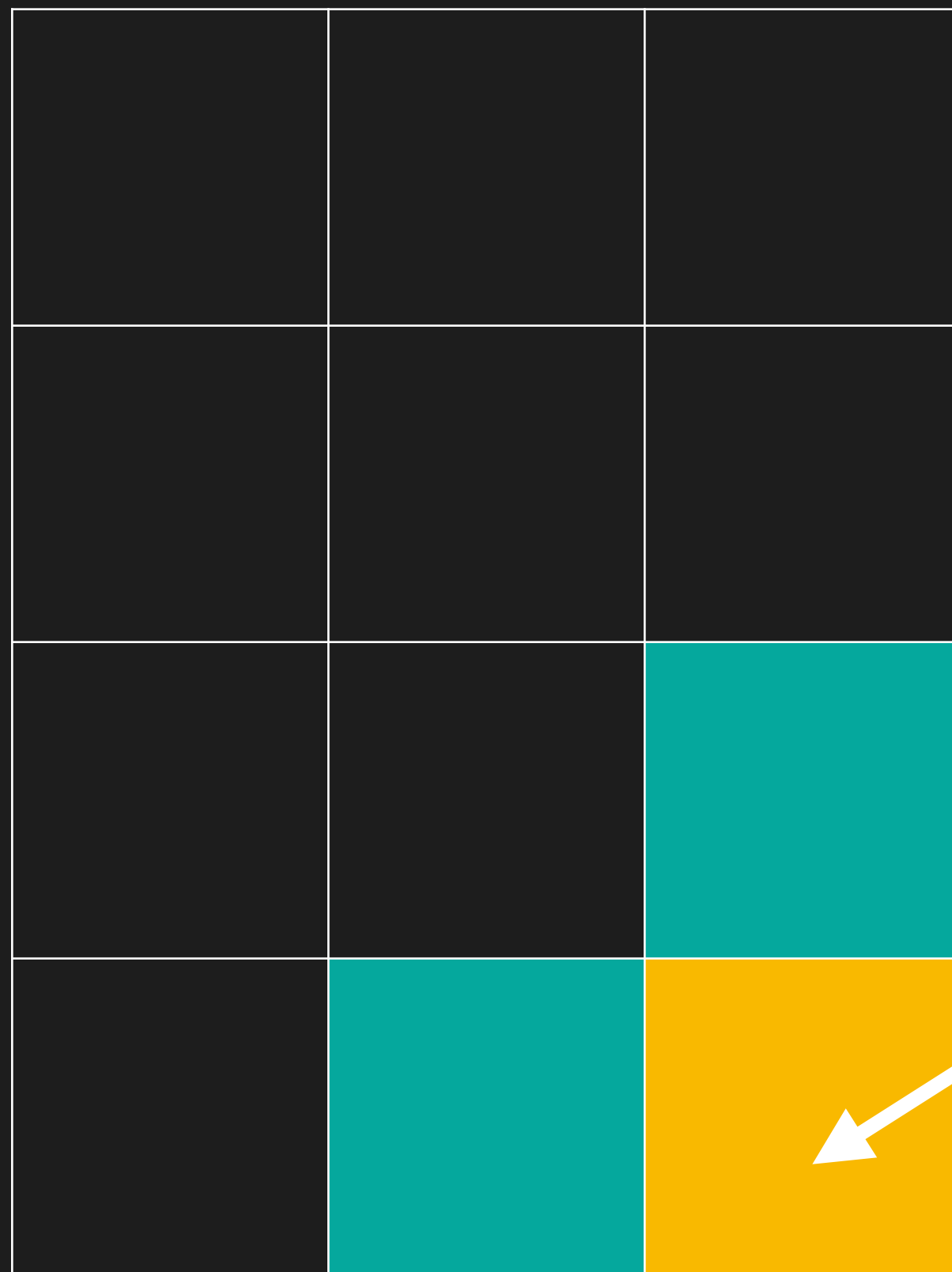
Defining the problem: smallest problem size

If either m or n is 0:
uniquePaths is 0

For a 1×1 , 1×2 , 2×1 board:
uniquePaths is 1



Unique Paths Optimal Substructure



To get to this cell, you can only come from top or left

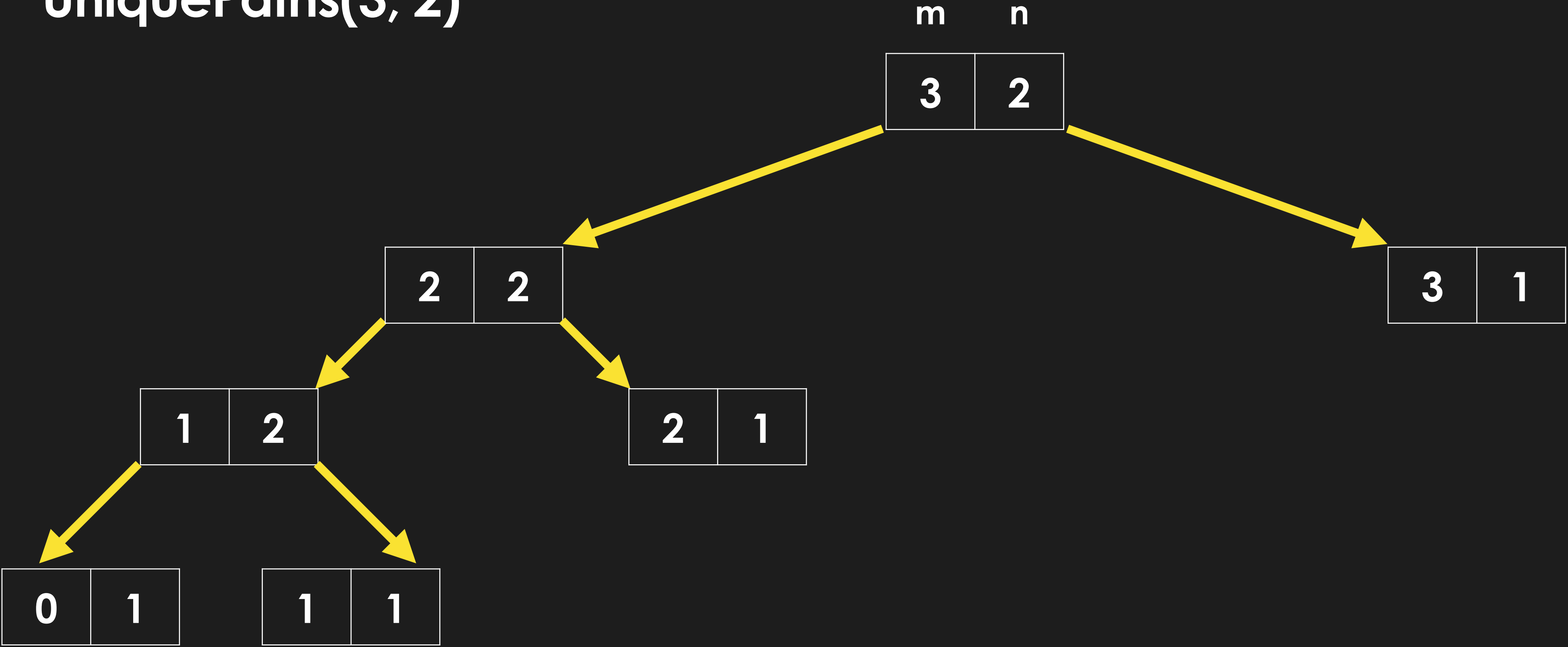
Hence, the total number of unique paths to the last cell will be:

Total number of unique paths to top cell + total number of unique paths to left cell

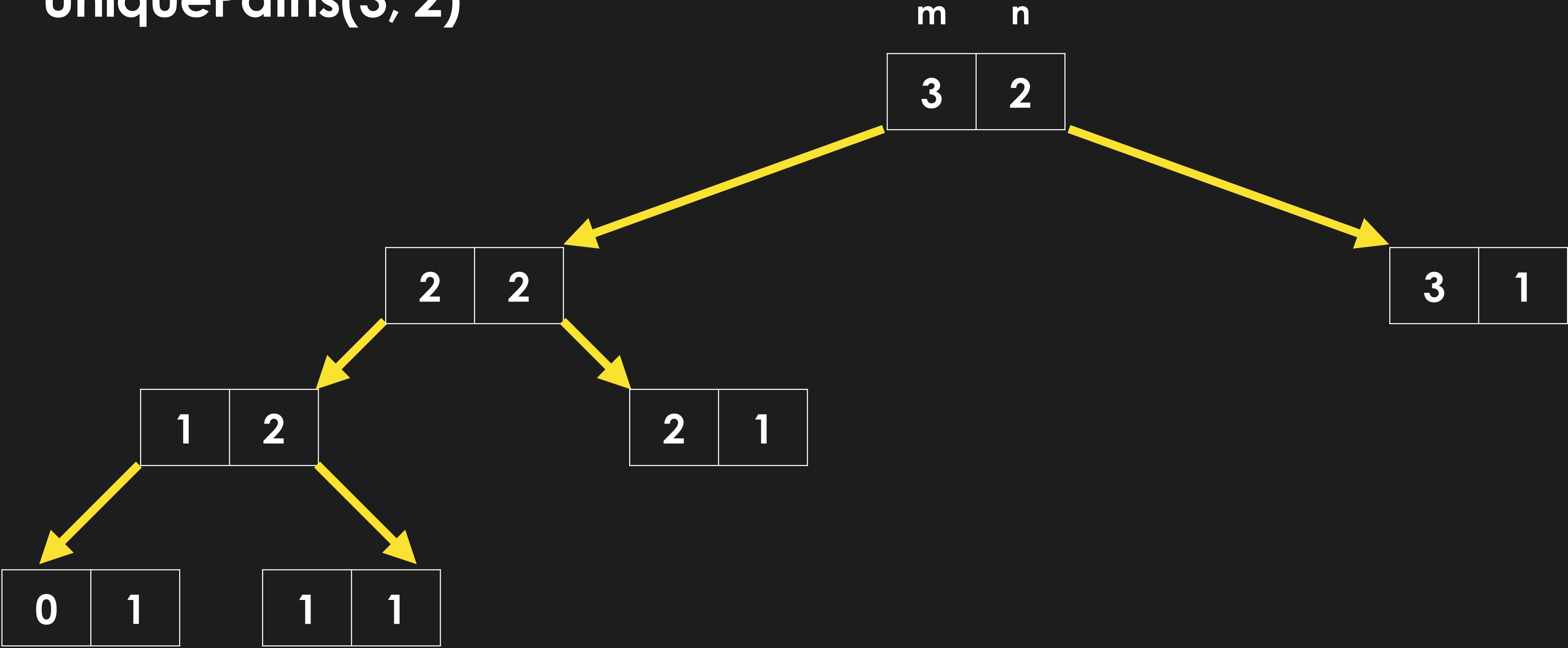
This is essentially the same as:

$$\text{uniquePaths}(m, n) = \text{uniquePaths}(m - 1, n) + \text{uniquePaths}(m, n - 1)$$

UniquePaths(3, 2)

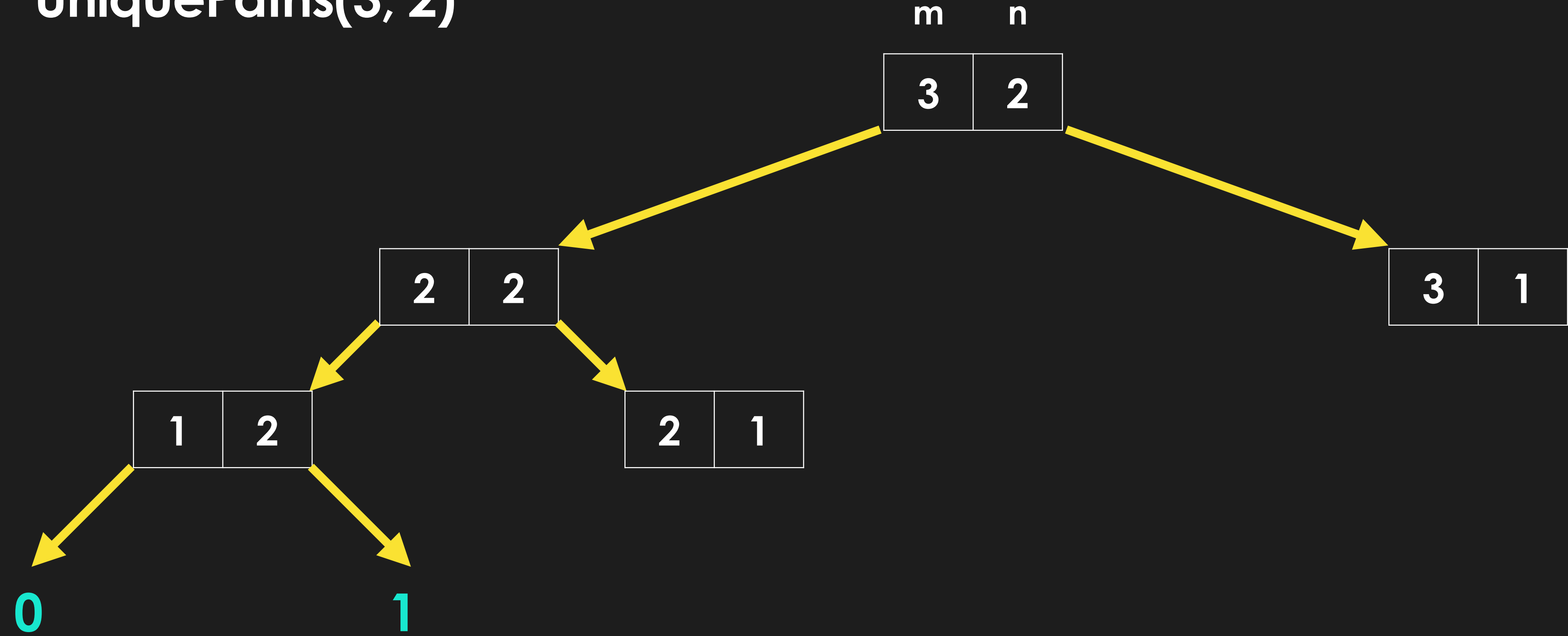


UniquePaths(3, 2)



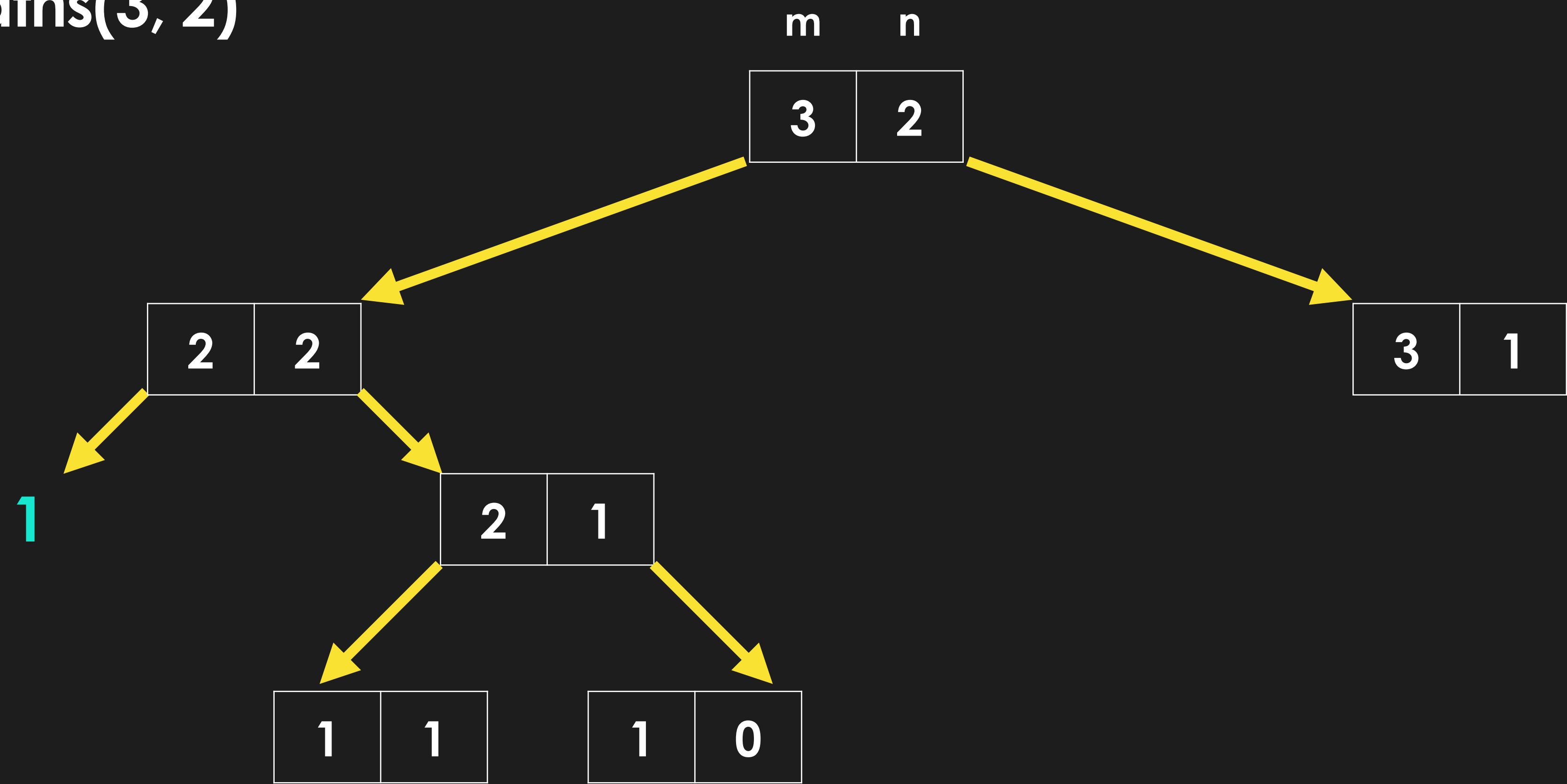
Base cases

UniquePaths(3, 2)



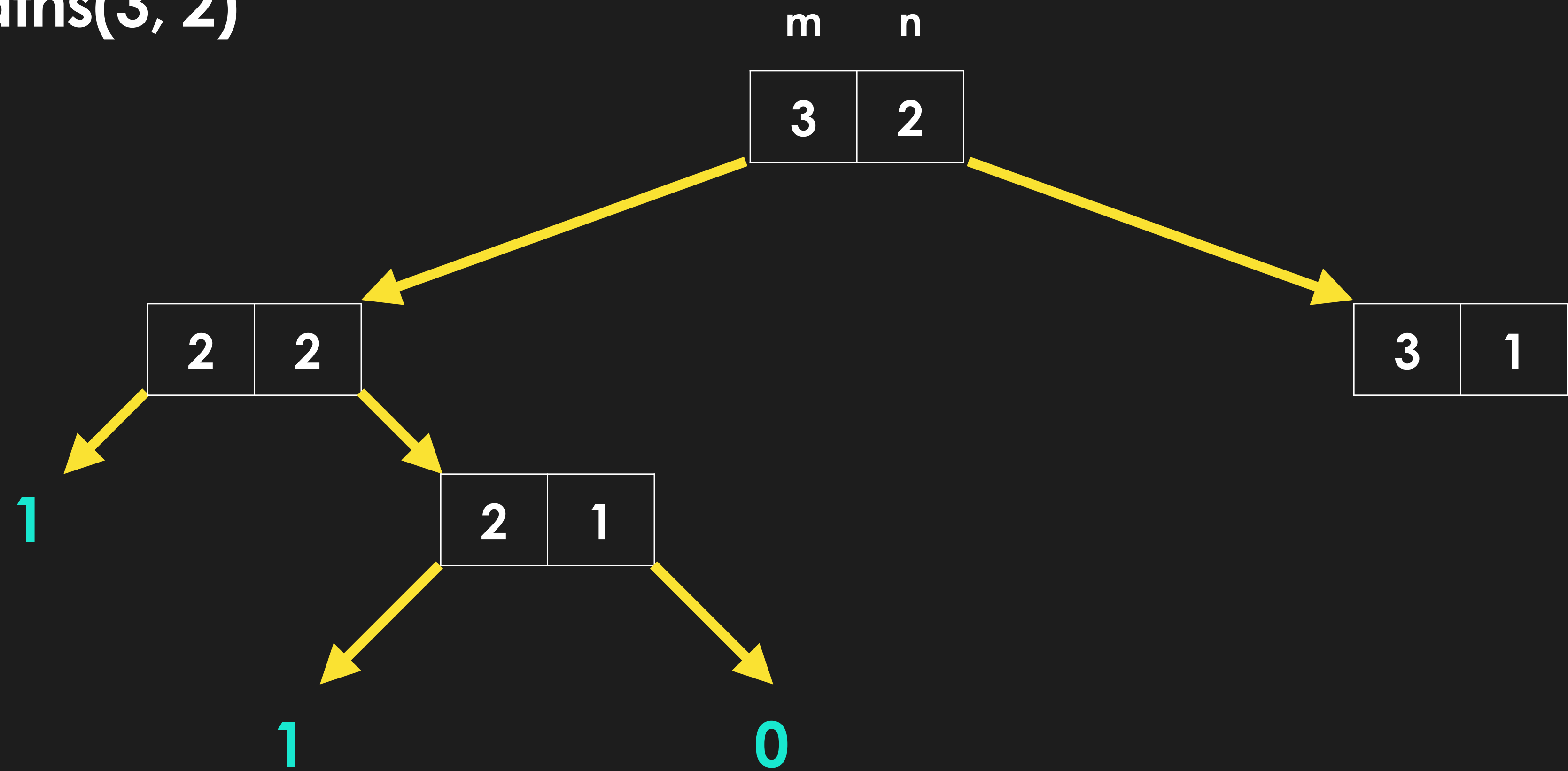
Base cases

UniquePaths(3, 2)



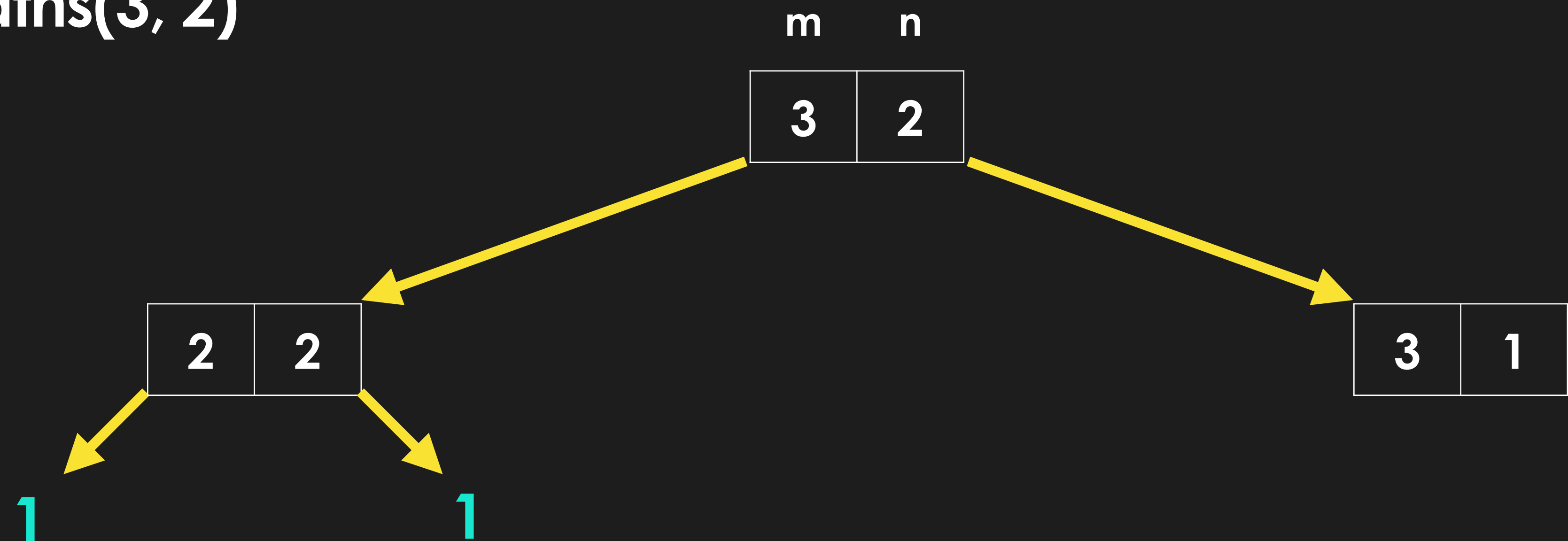
Base cases

UniquePaths(3, 2)



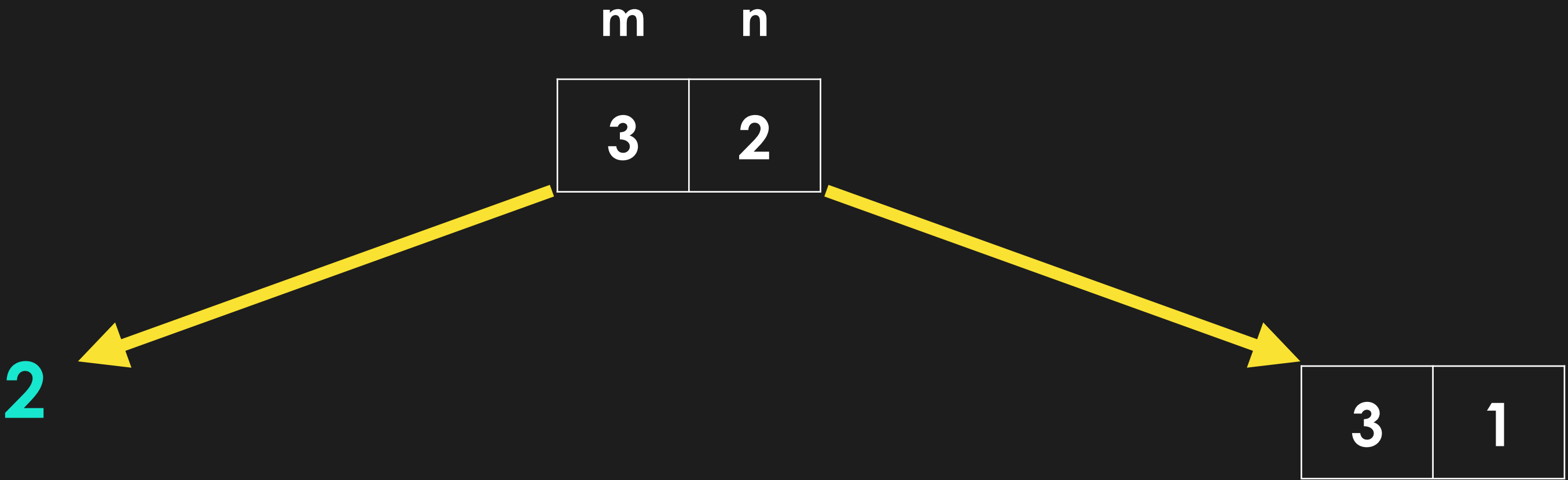
Base cases

UniquePaths(3, 2)



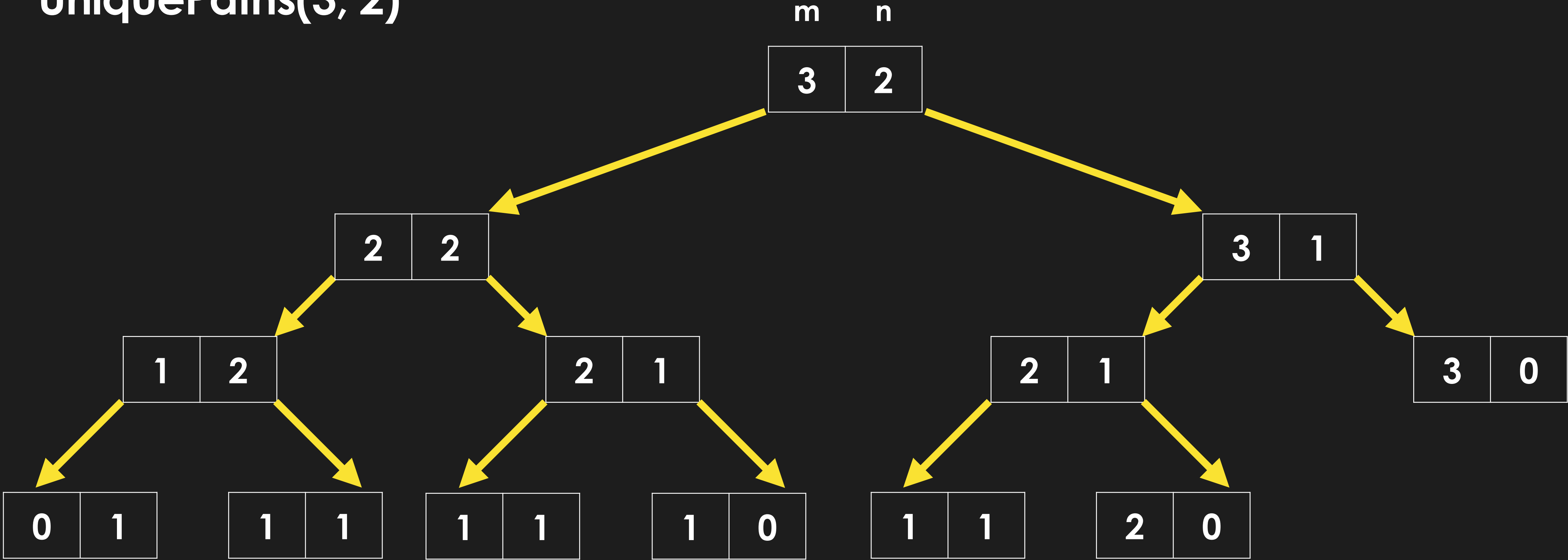
Base cases

UniquePaths(3, 2)

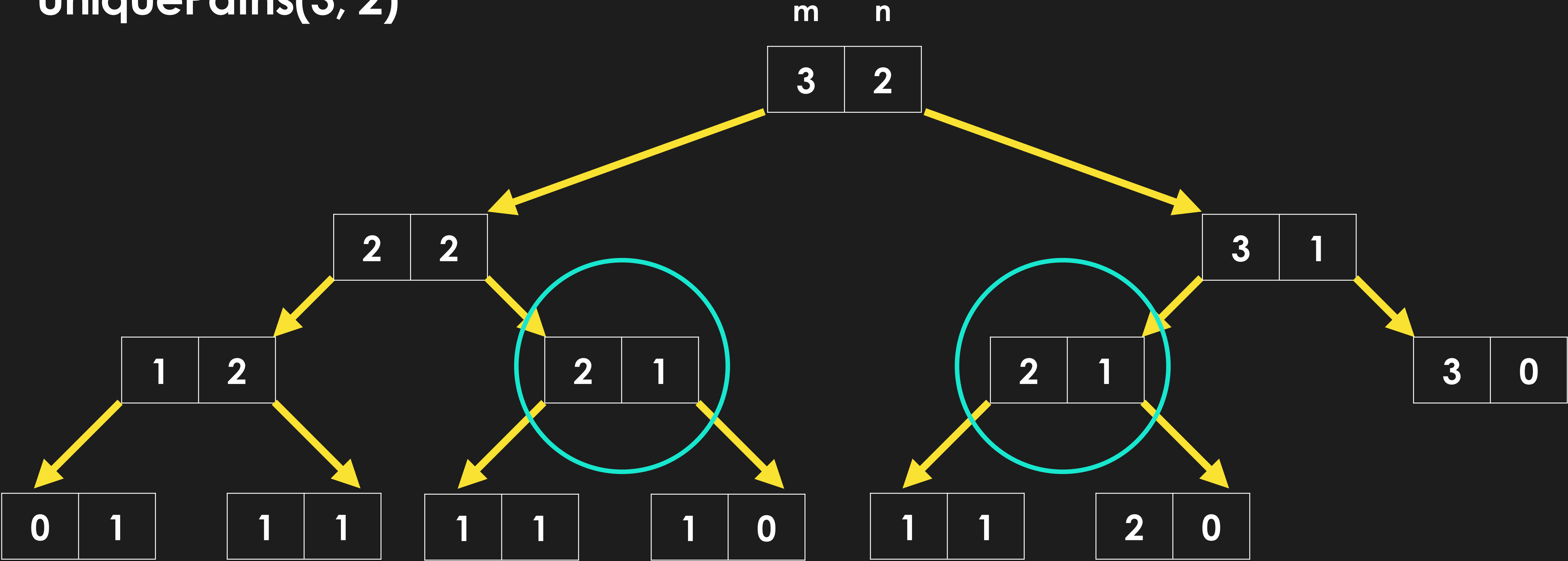


Base cases

UniquePaths(3, 2)

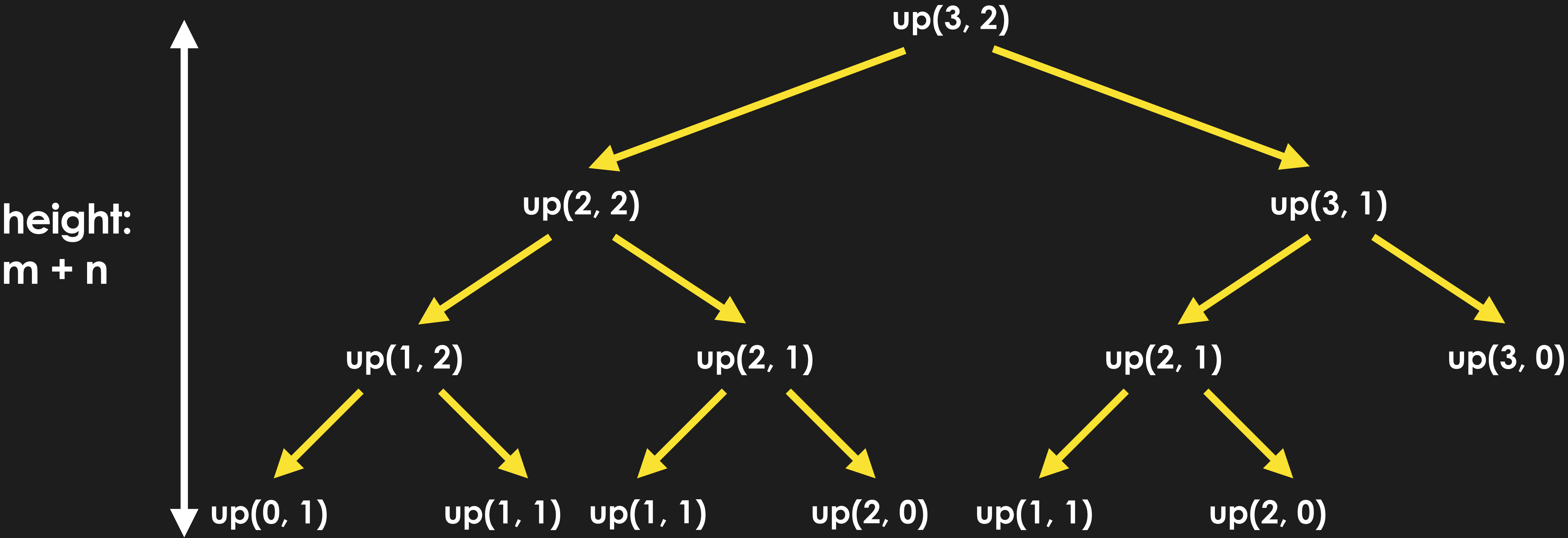


UniquePaths(3, 2)

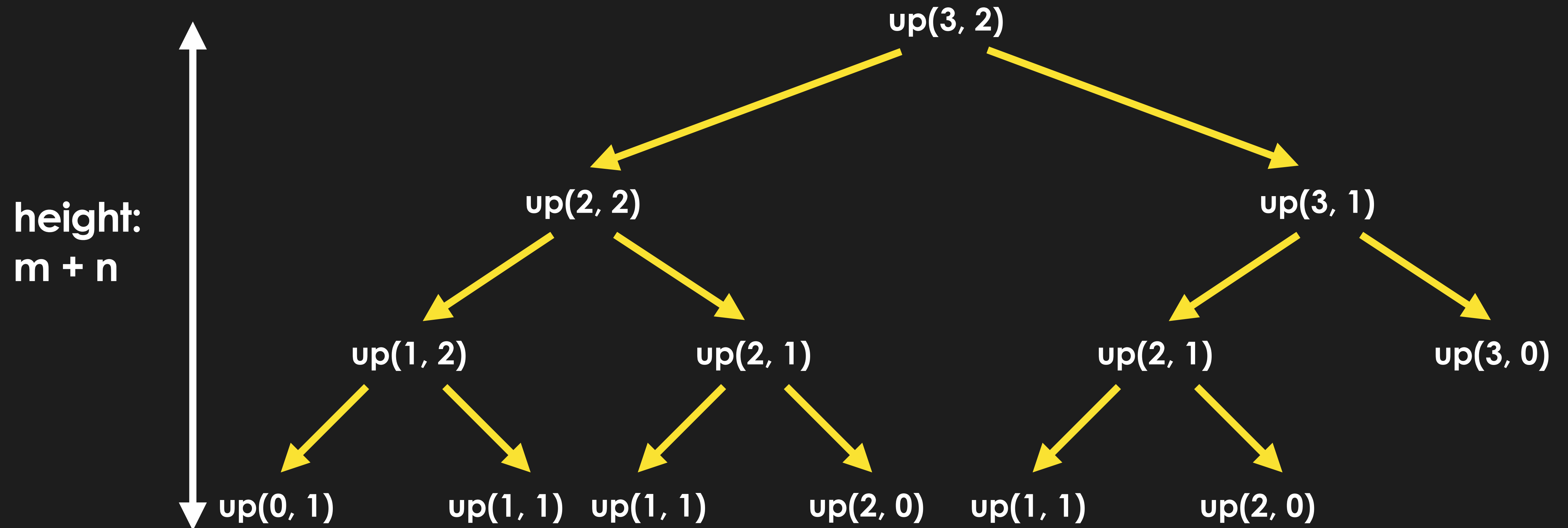


Overlapping subproblems

UniquePaths(3, 2)



UniquePaths(3, 2)



Time Complexity: 2^{m+n}

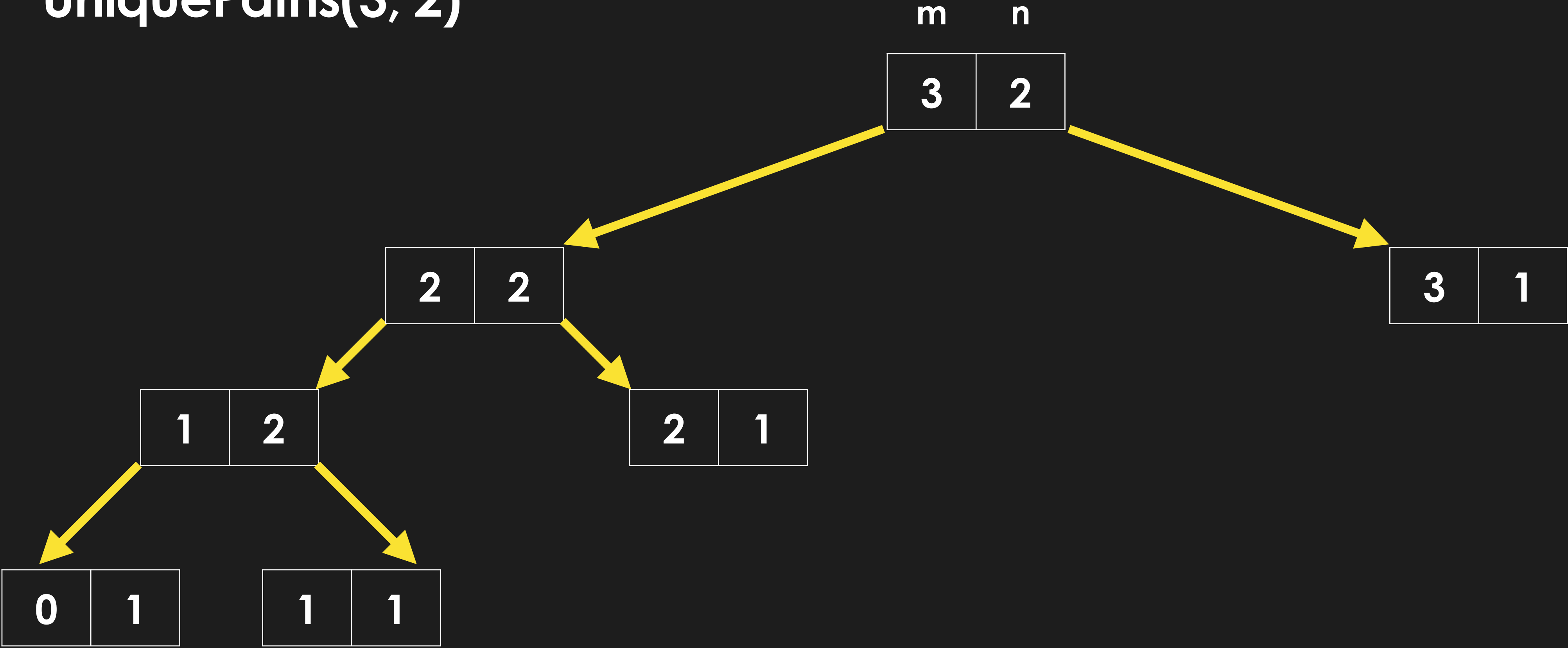
Space Complexity: $m + n$

Unique Paths

```
def uniquePaths(m, n):  
    if m == 0 or n == 0:  
        return 0  
    elif m == 1 and n == 1:  
        return 1  
    else:  
        return uniquePaths(m - 1, n) + uniquePaths(m, n - 1)
```

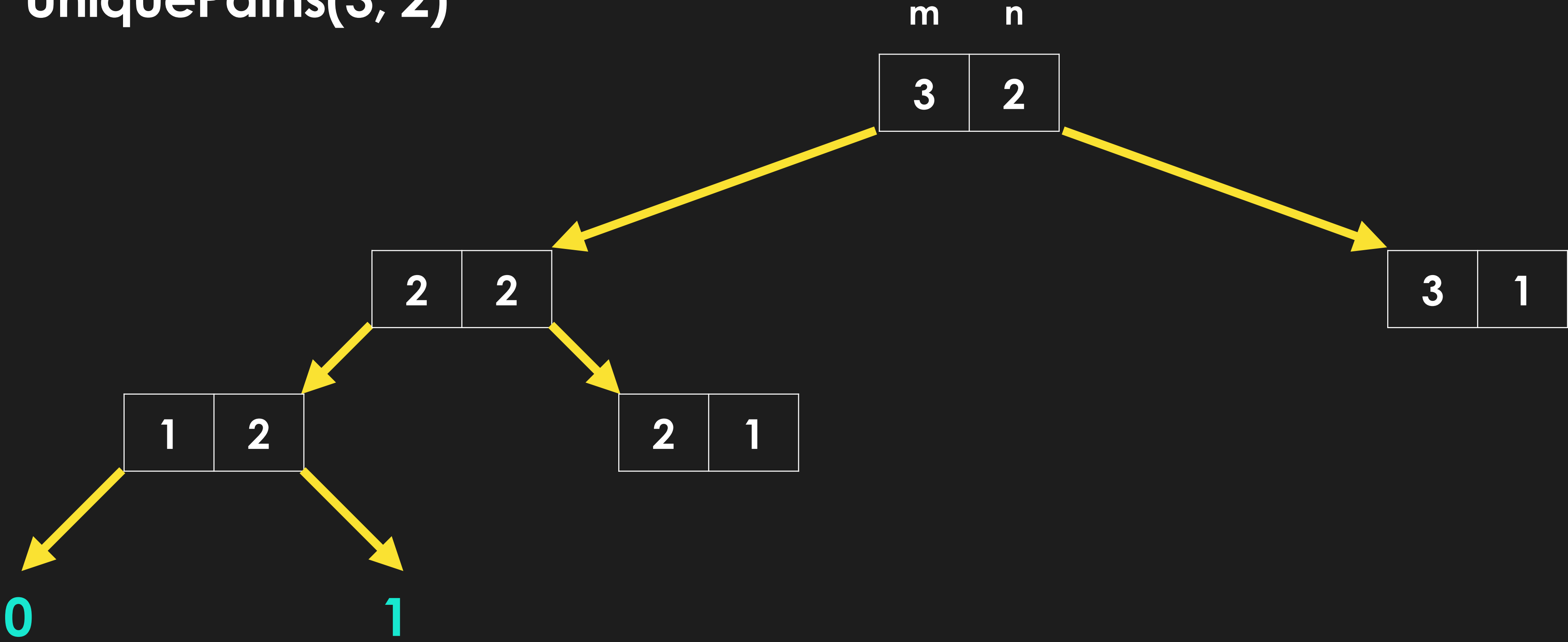
Memoization

UniquePaths(3, 2)



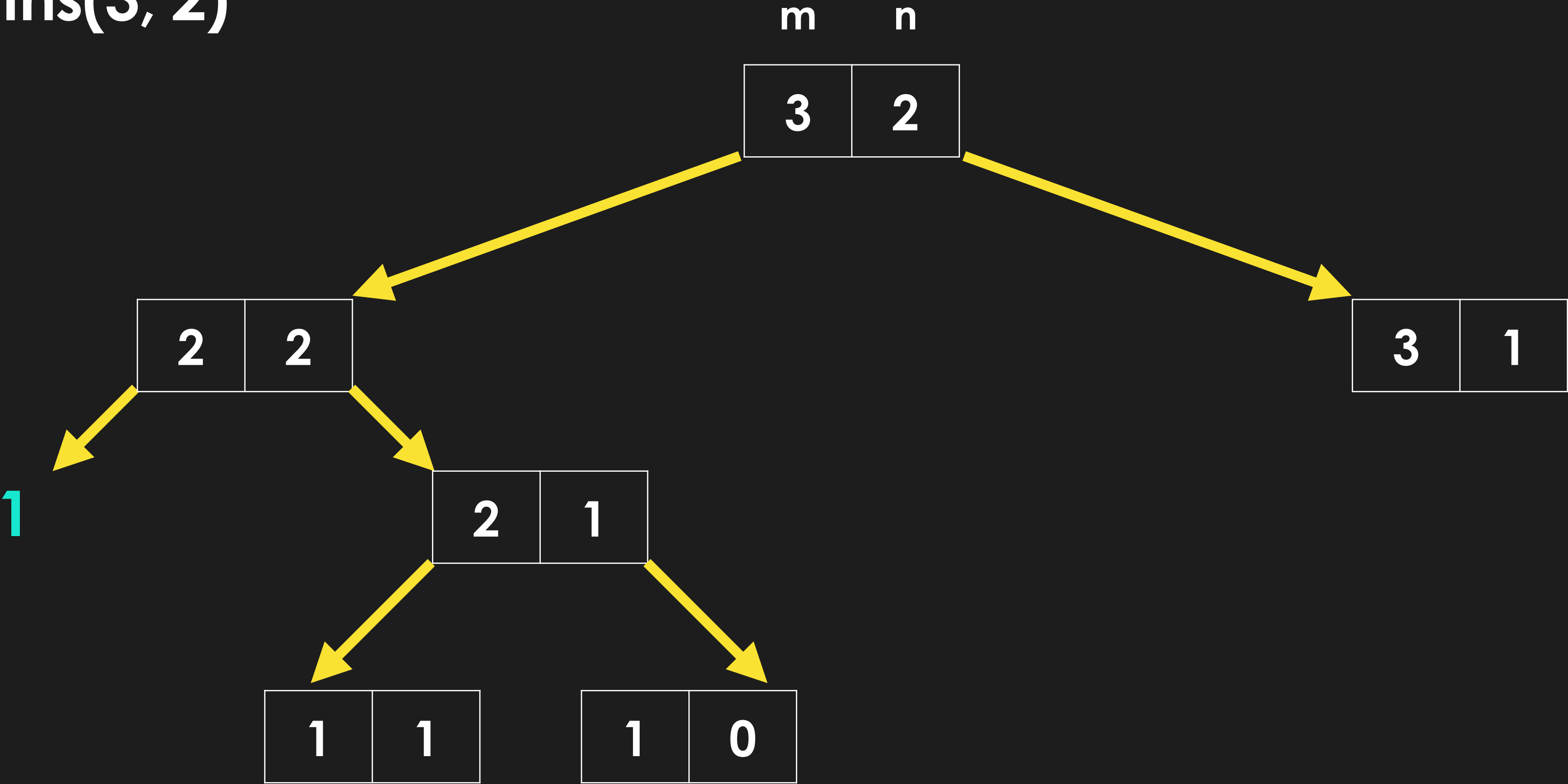
(m, n)					
memo					

UniquePaths(3, 2)



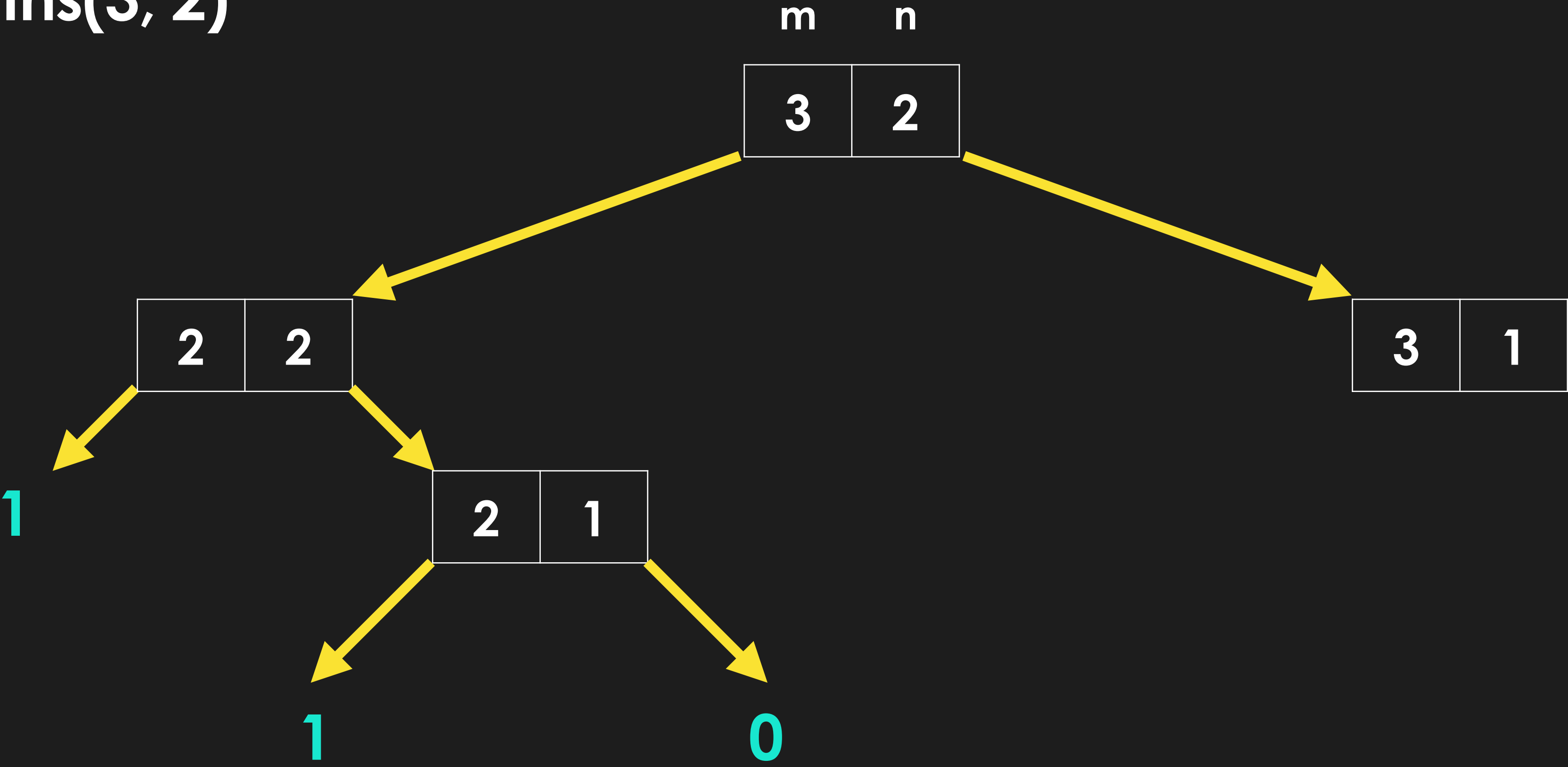
(m, n)					
memo					

UniquePaths(3, 2)



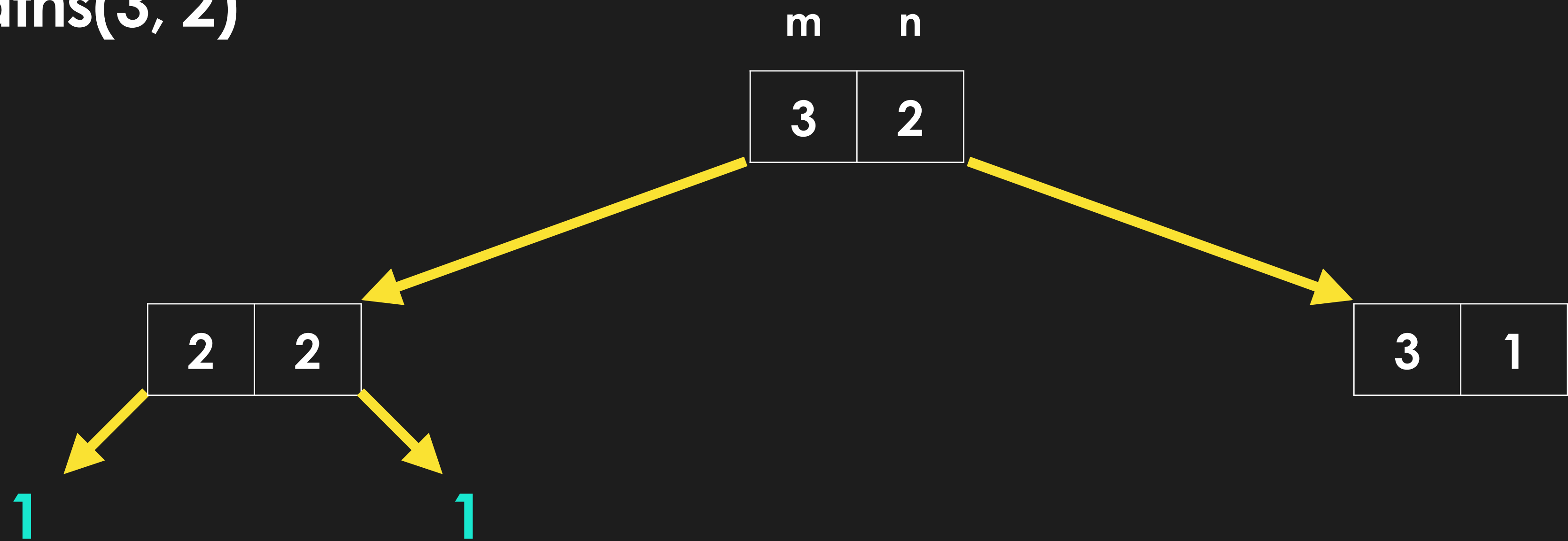
(m, n)	(1, 2)				
memo	1				

UniquePaths(3, 2)



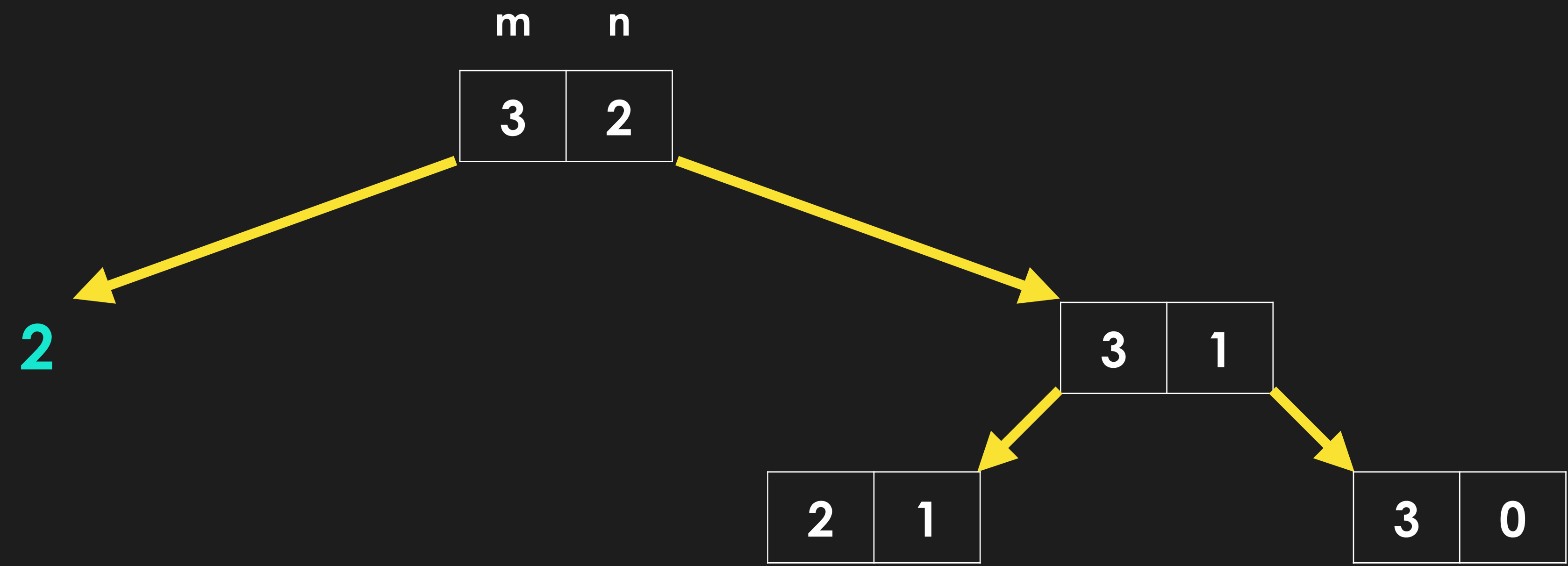
(m, n)	(1, 2)				
memo	1				

UniquePaths(3, 2)



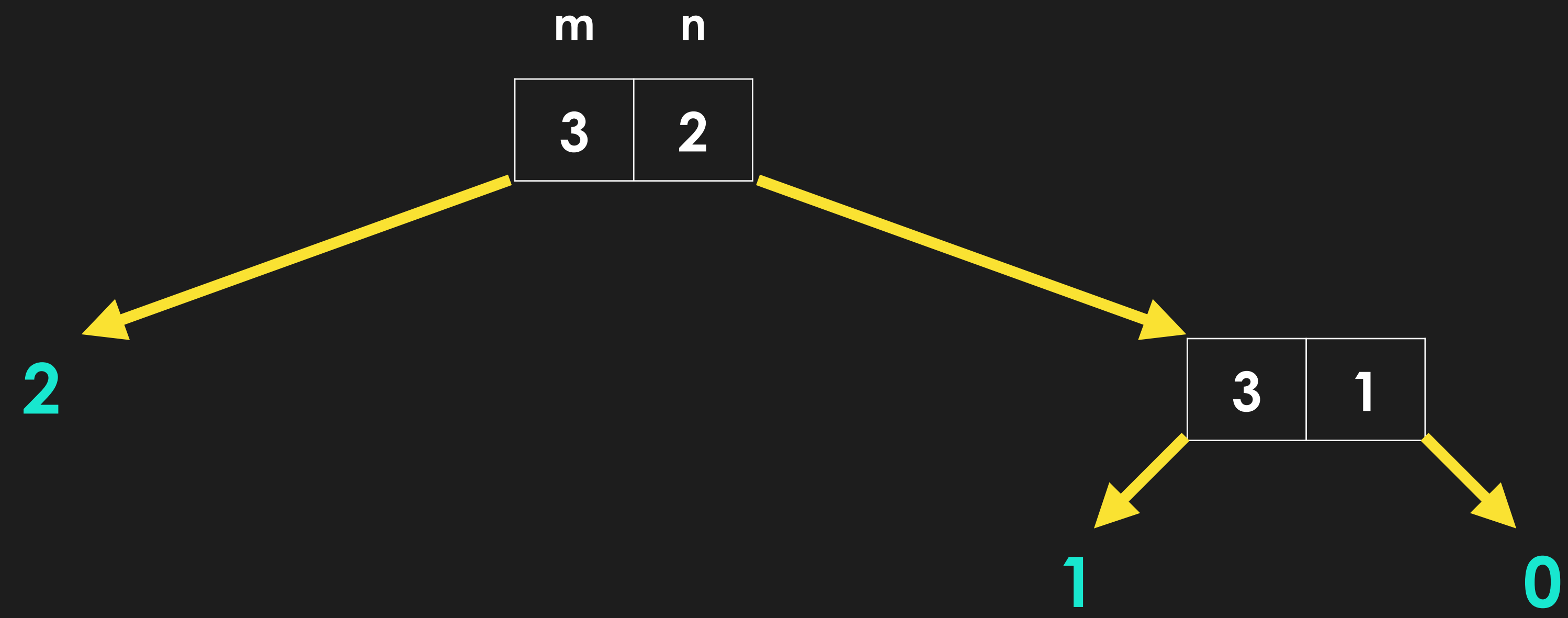
(m, n)	(1, 2)	(2, 1)			
memo	1	1			

UniquePaths(3, 2)



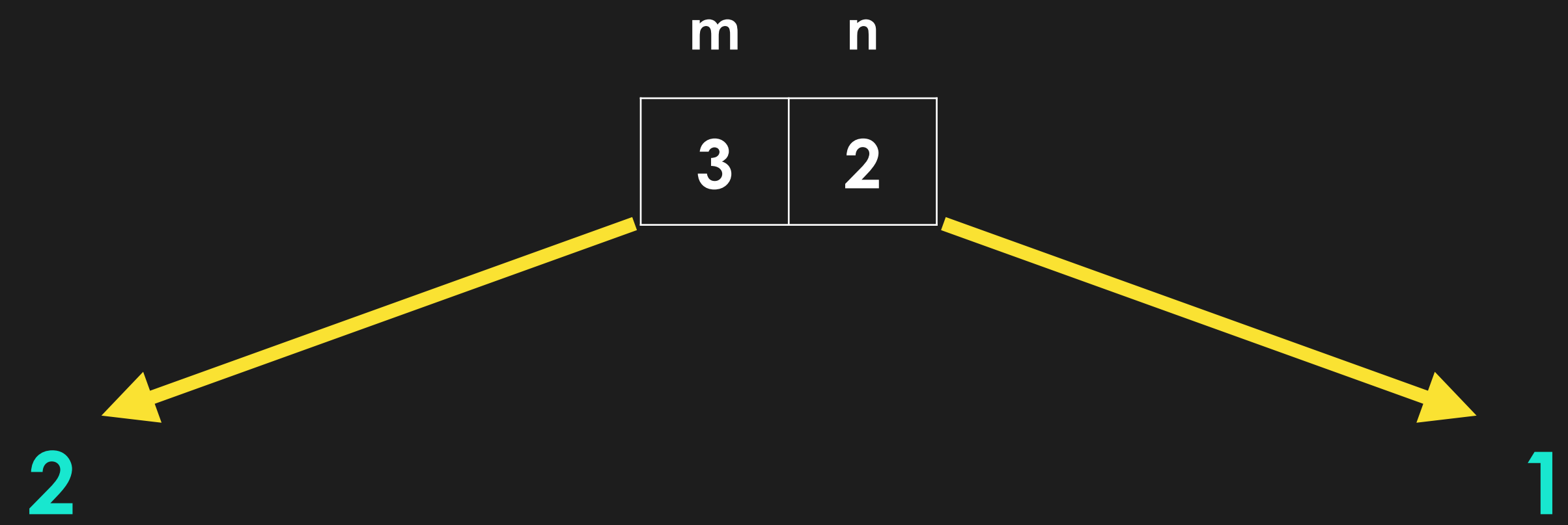
(m, n)	(1, 2)	(2, 1)	(2, 2)		
memo	1	1	2		

UniquePaths(3, 2)



(m, n)	(1, 2)	(2, 1)	(2, 2)		
memo	1	1	2		

UniquePaths(3, 2)



(m, n)	(1, 2)	(2, 1)	(2, 2)	(3, 1)	
memo	1	1	2	1	

UniquePaths(3, 2)

m n
3

(m, n)	(1, 2)	(2, 1)	(2, 2)	(3, 1)	(3, 2)
memo	1	1	2	1	3

Unique Paths Memo

```
memo = {}

def uniquePathsMemo(m, n):
    if m == 0 or n == 0:
        return 0
    elif m == 1 and n == 1:
        return 1
    elif (m, n) in memo:
        return memo[(m, n)]

    else:
        cost = uniquePathsMemo(m - 1, n) + uniquePathsMemo(m, n - 1)
        memo[(m, n)] = cost
        memo[(n, m)] = cost
        return cost
```

DP Problem #3: Can Sum

Can Sum

Given an array of integers, and a target sum, print out whether there exists a combination of the array of numbers, with repetition, that adds to the target sum

Can Sum

Given an array of integers, and a target sum, print out whether there exists a combination of the array of numbers, with repetition, that adds to the target sum

Example:

array: [3, 6, 7]

target: 10

canSum: True

combinations: [5, 5]

Can Sum

Given an array of integers, and a target sum, print out whether there exists a combination of the array of numbers, with repetition, that adds to the target sum

Example:

array: [3, 6, 7]

target: 10

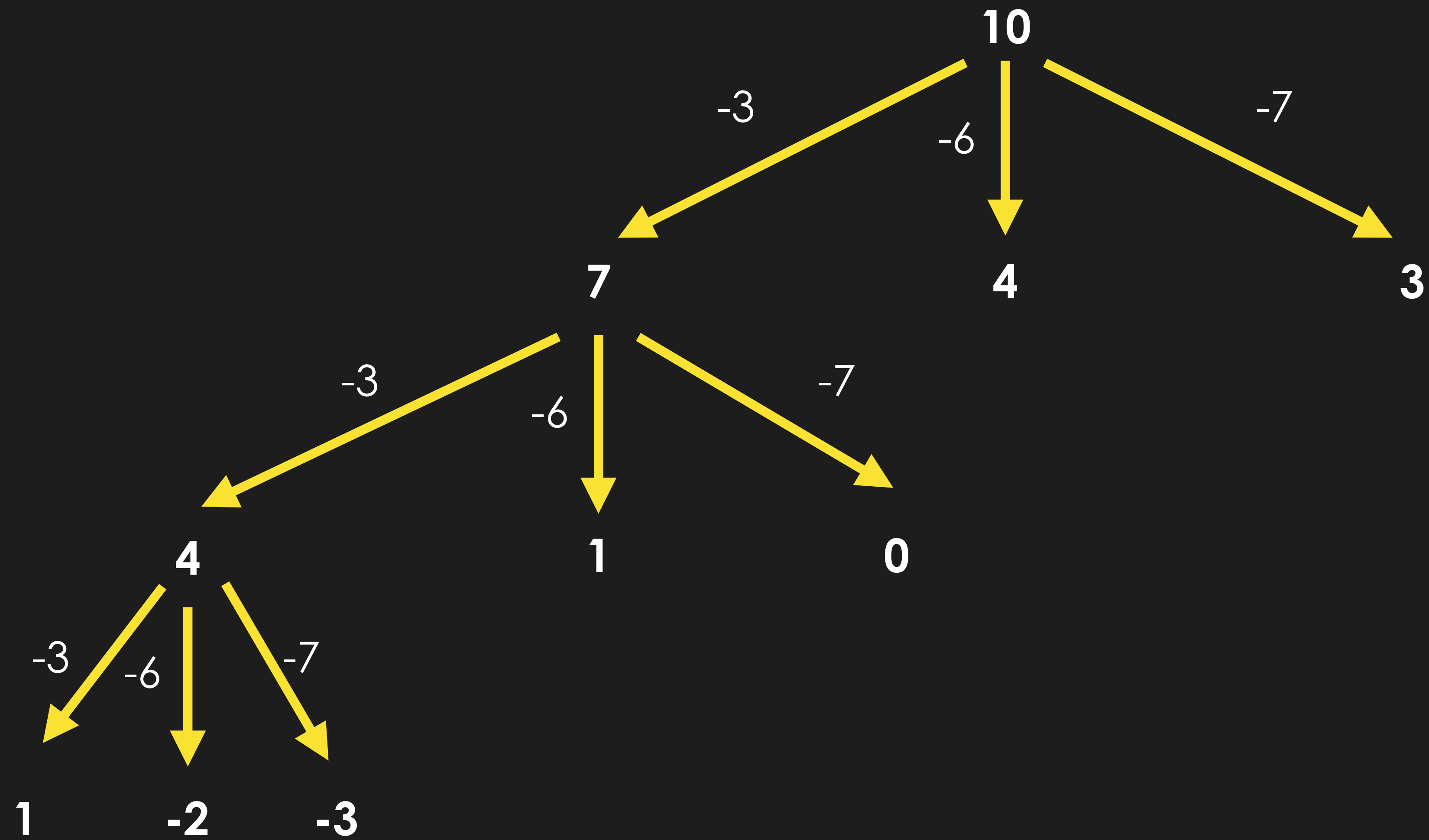
canSum: True

combinations: [5, 5]

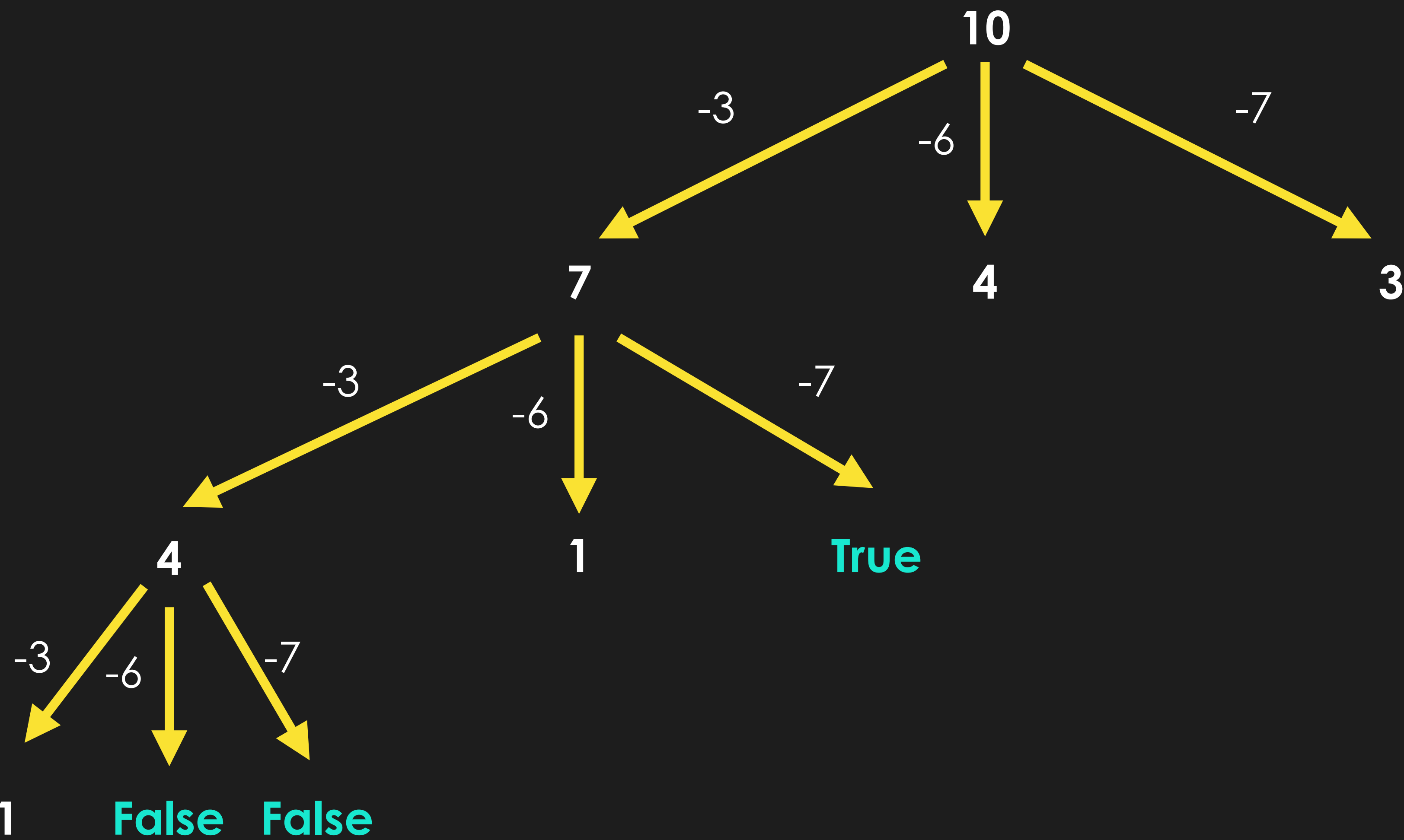
Optimal Substructure

If **canSum(array, target - array[i])** is **True**
where *i* is a valid index in the array, then
canSum(array, target) is **True**

CanSum

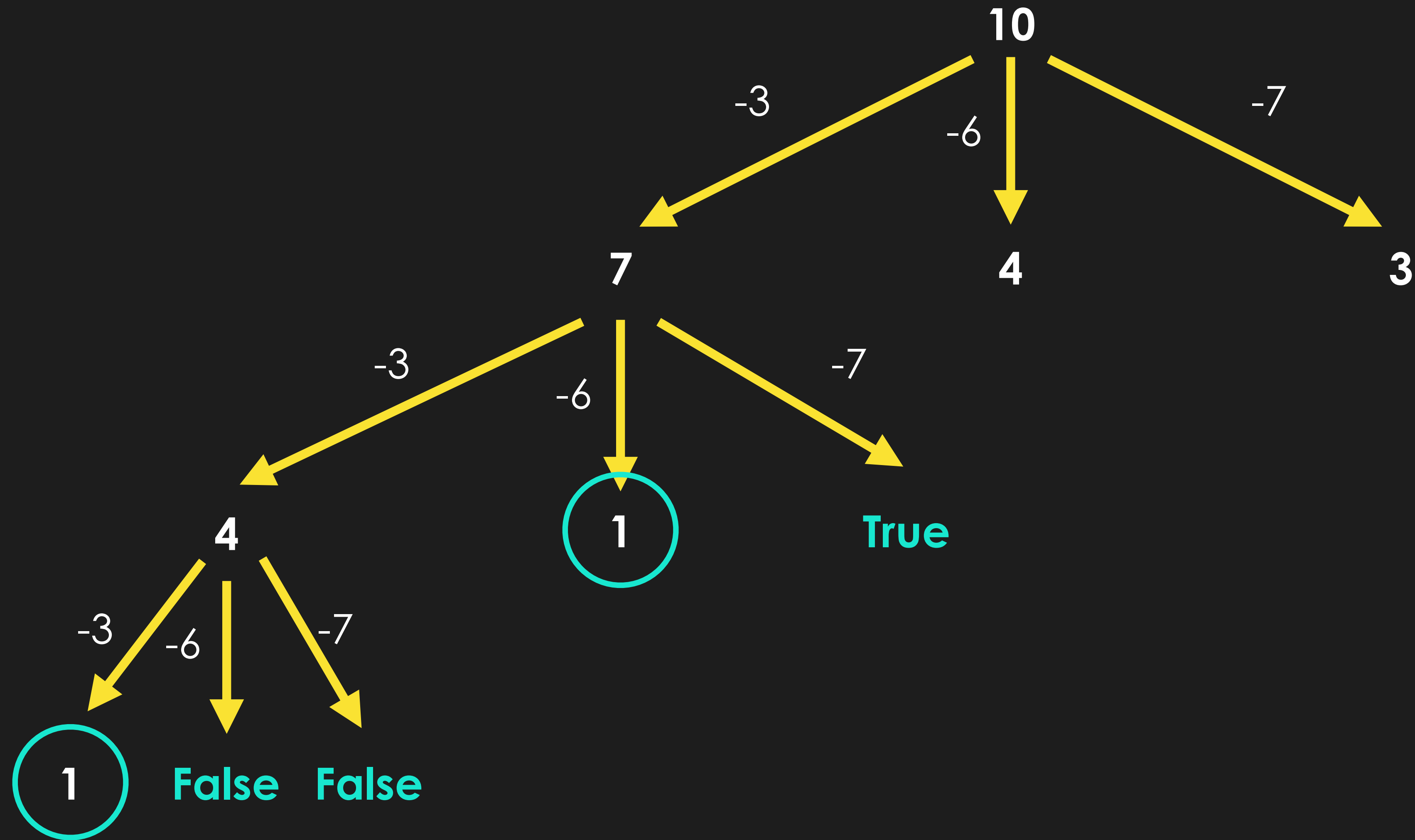


CanSum



Base case

CanSum

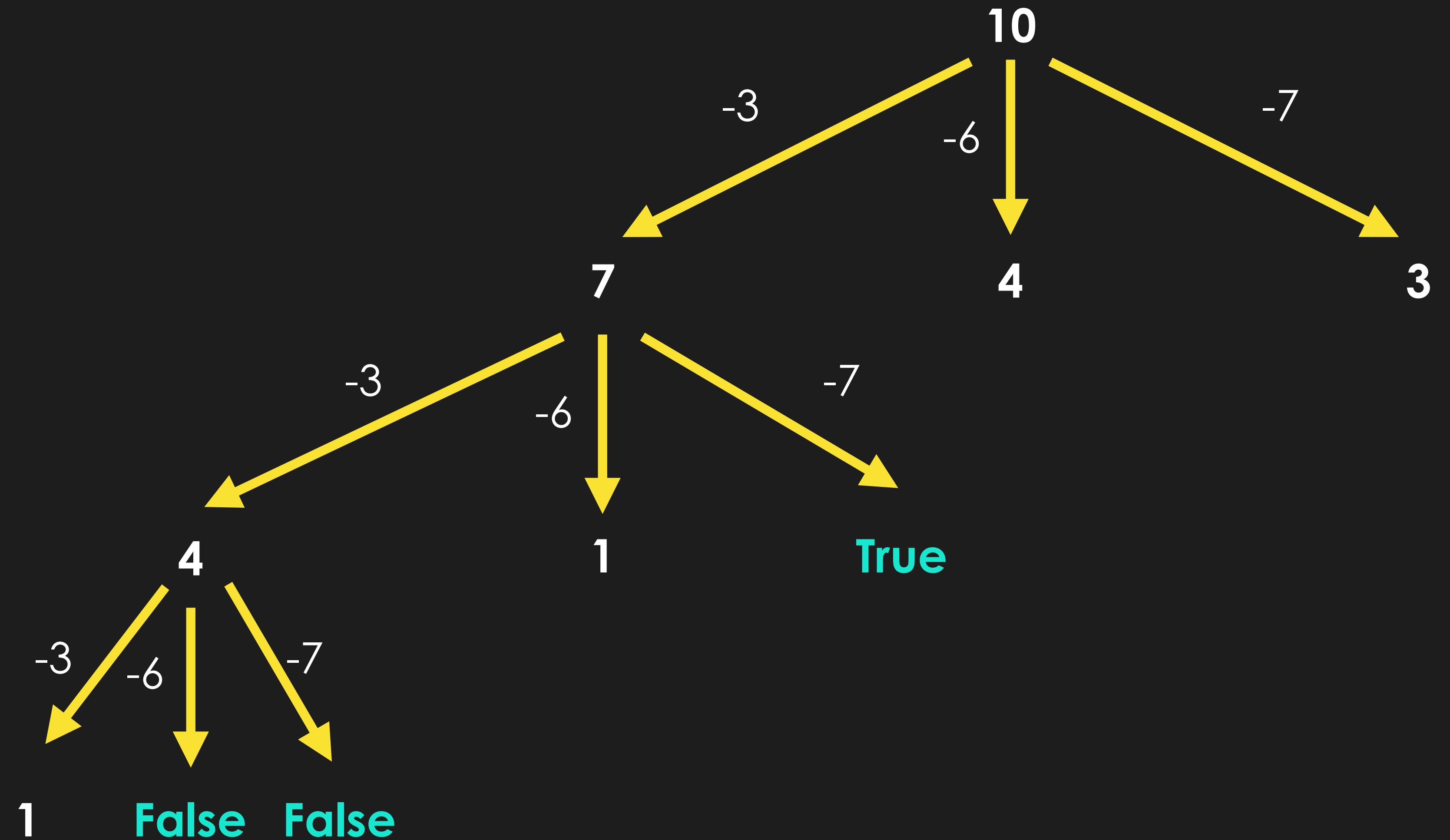


Overlapping subproblem!

CanSum

n: length of array

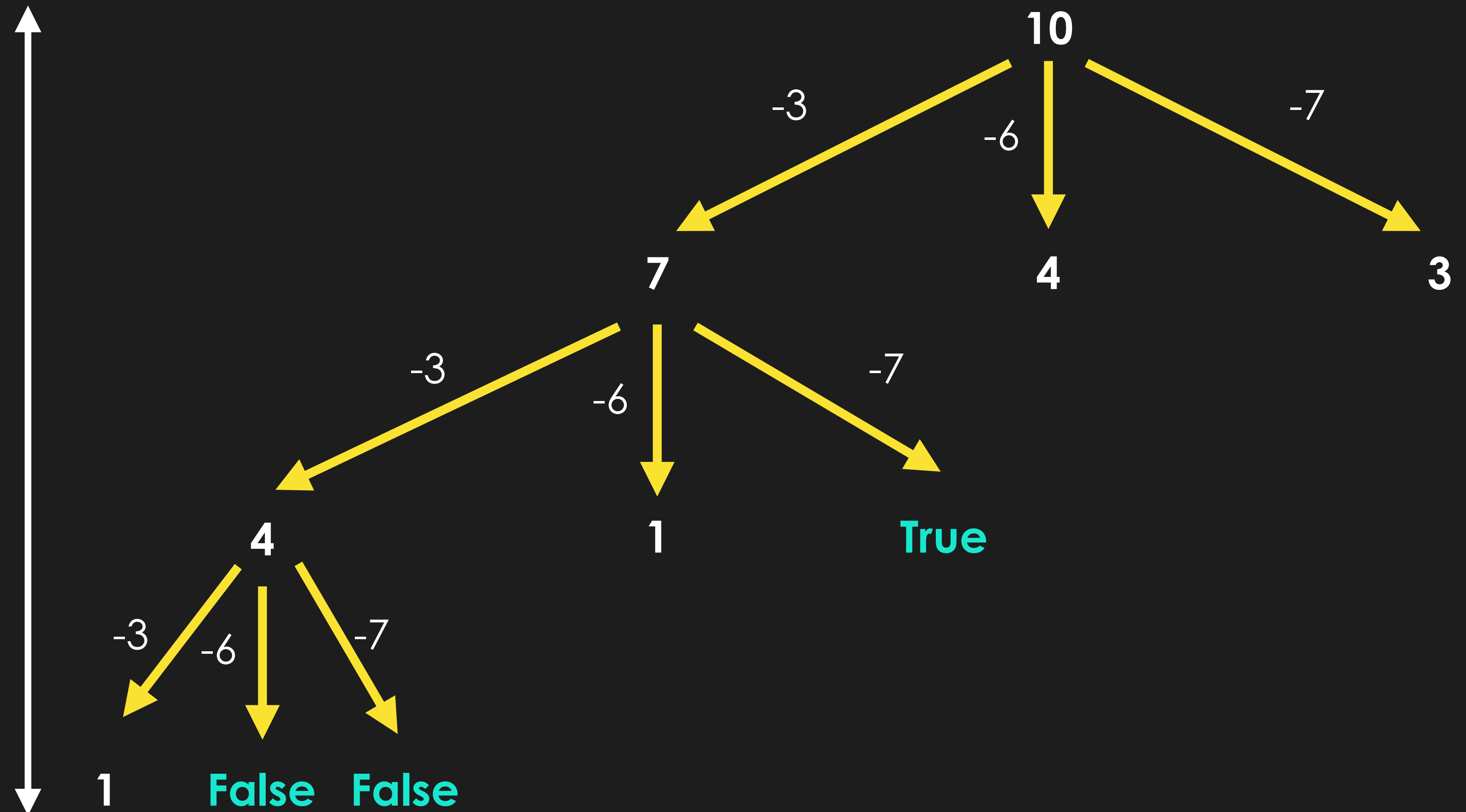
m: target sum



CanSum

n: length of array
m: target sum

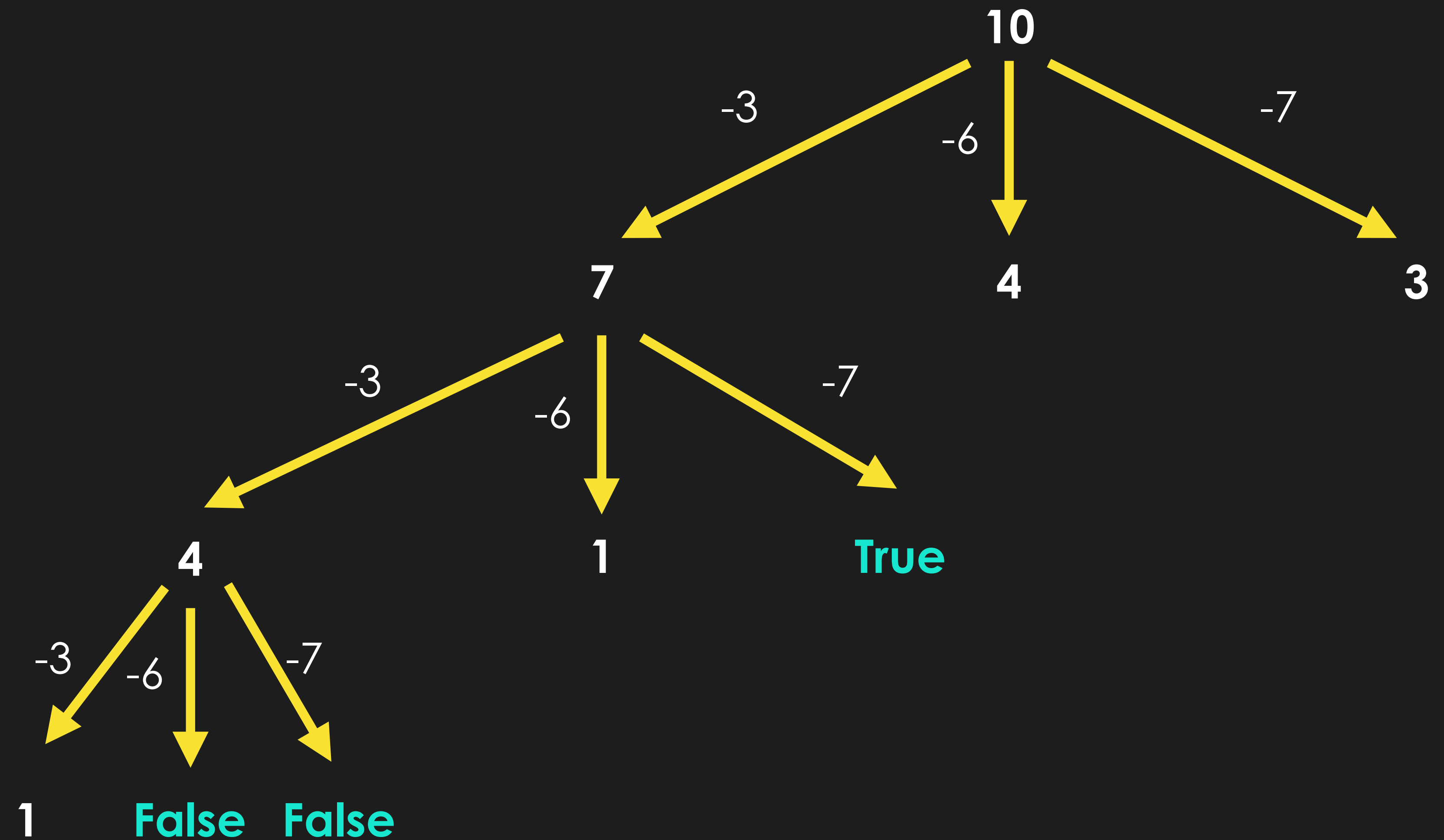
height: m



CanSum

n: length of array
m: target sum

height: m



Time Complexity: n^m

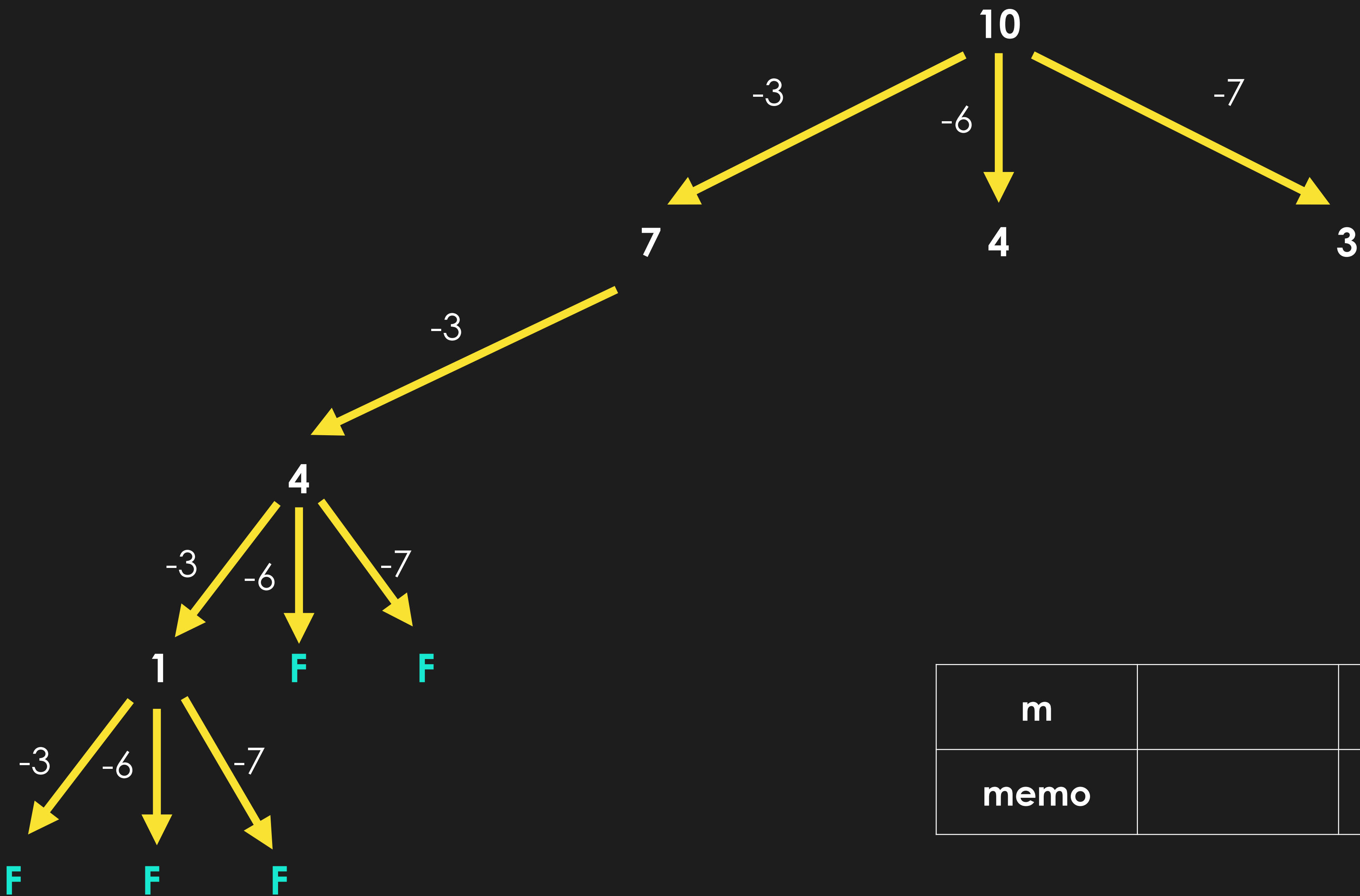
Space Complexity: m

CanSum

```
def CanSum(array, target):  
    if target == 0:  
        return 1  
    if target < 0:  
        return 0  
  
    for i in array:  
        newTarget = target - i  
        if (CanSum(array, newTarget)):  
            return True  
  
    return False
```

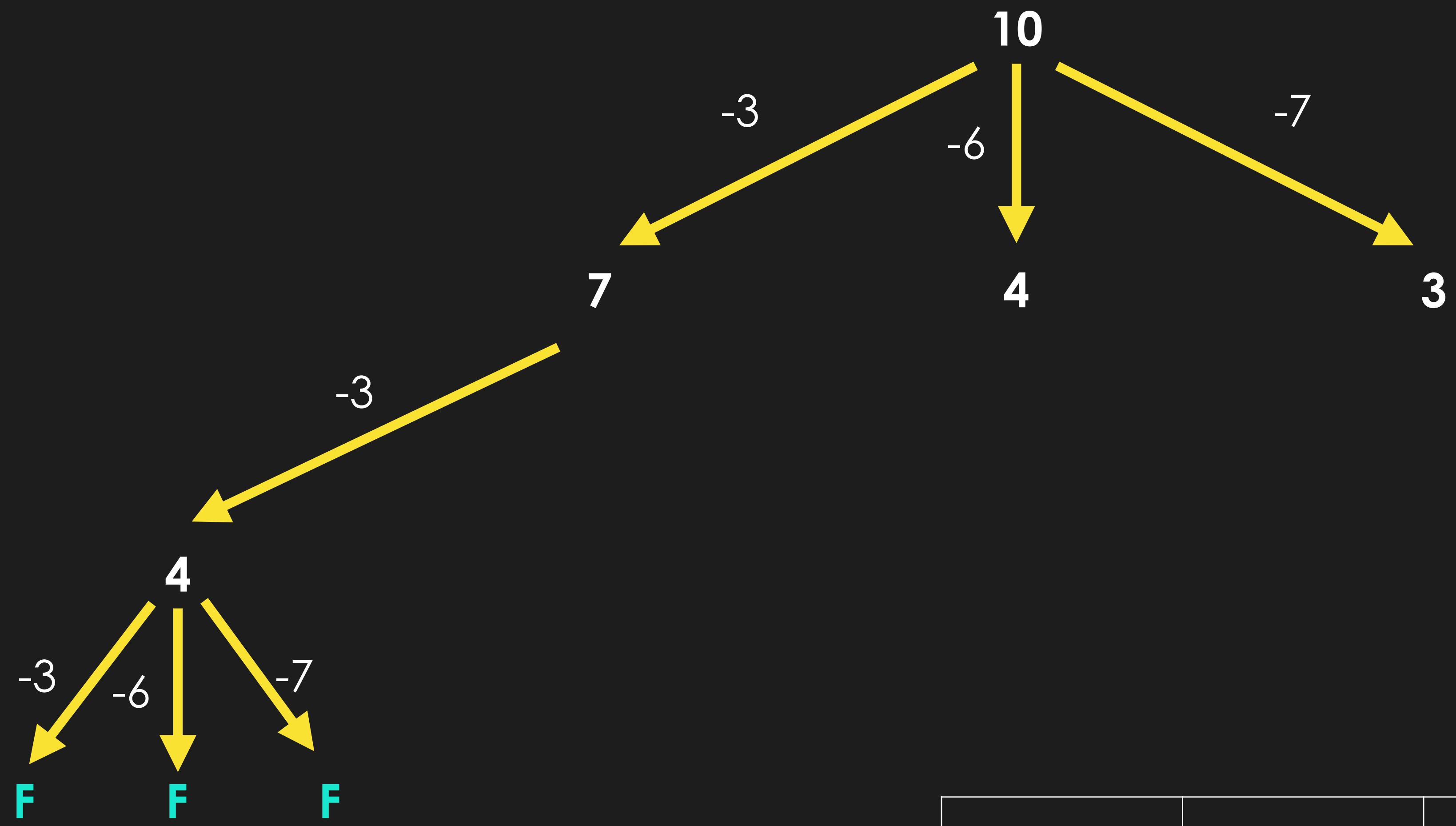
Memoization!

CanSumMemo



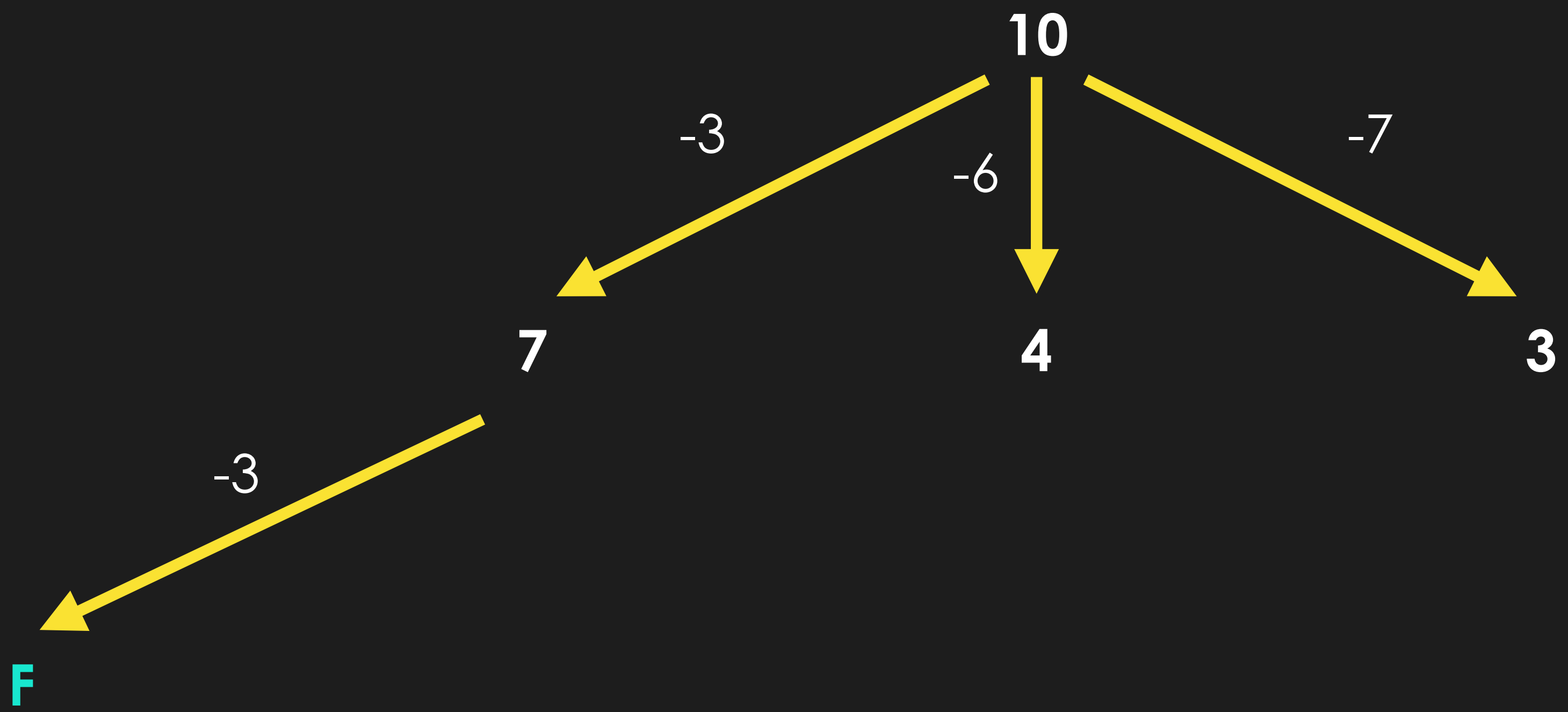
m			
memo			

CanSumMemo



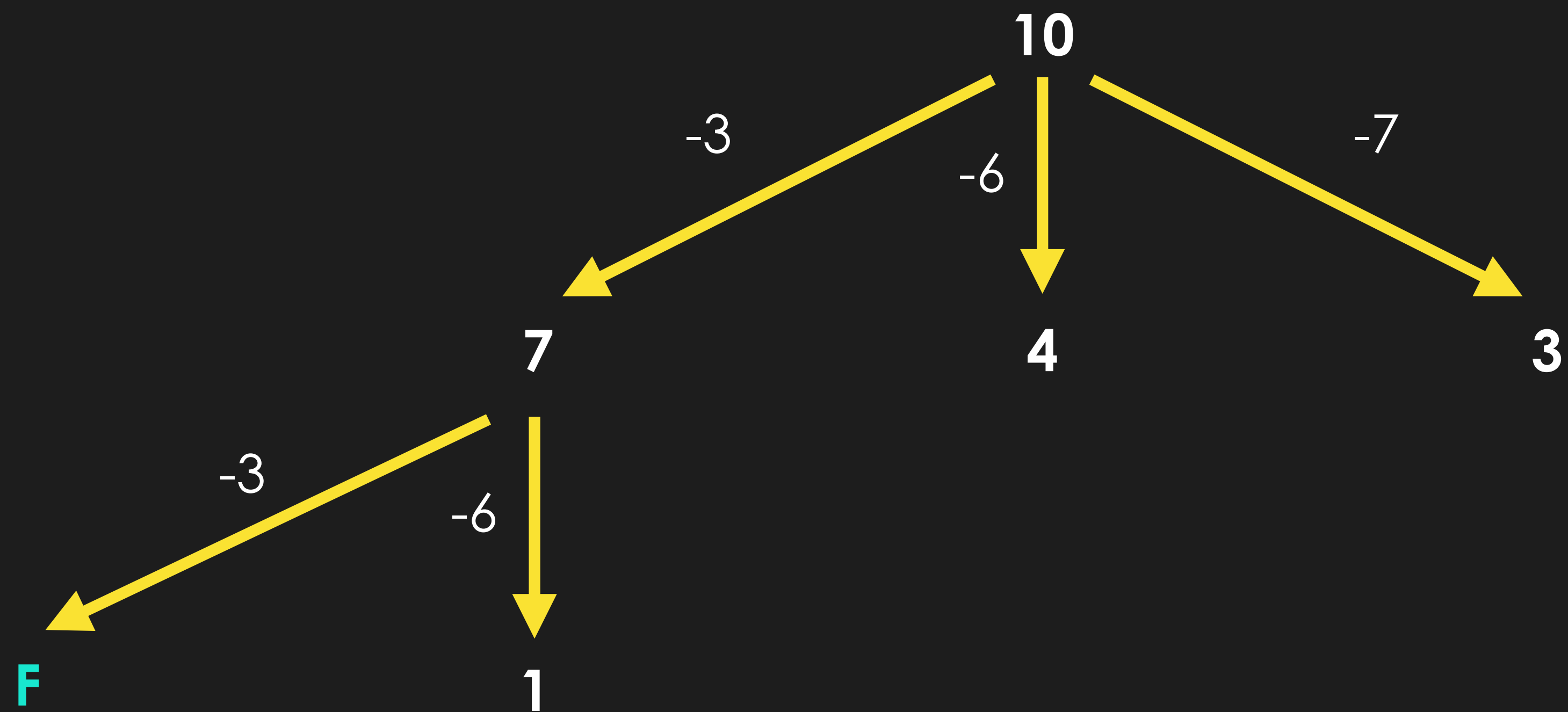
m	1		
memo	FALSE		

CanSumMemo



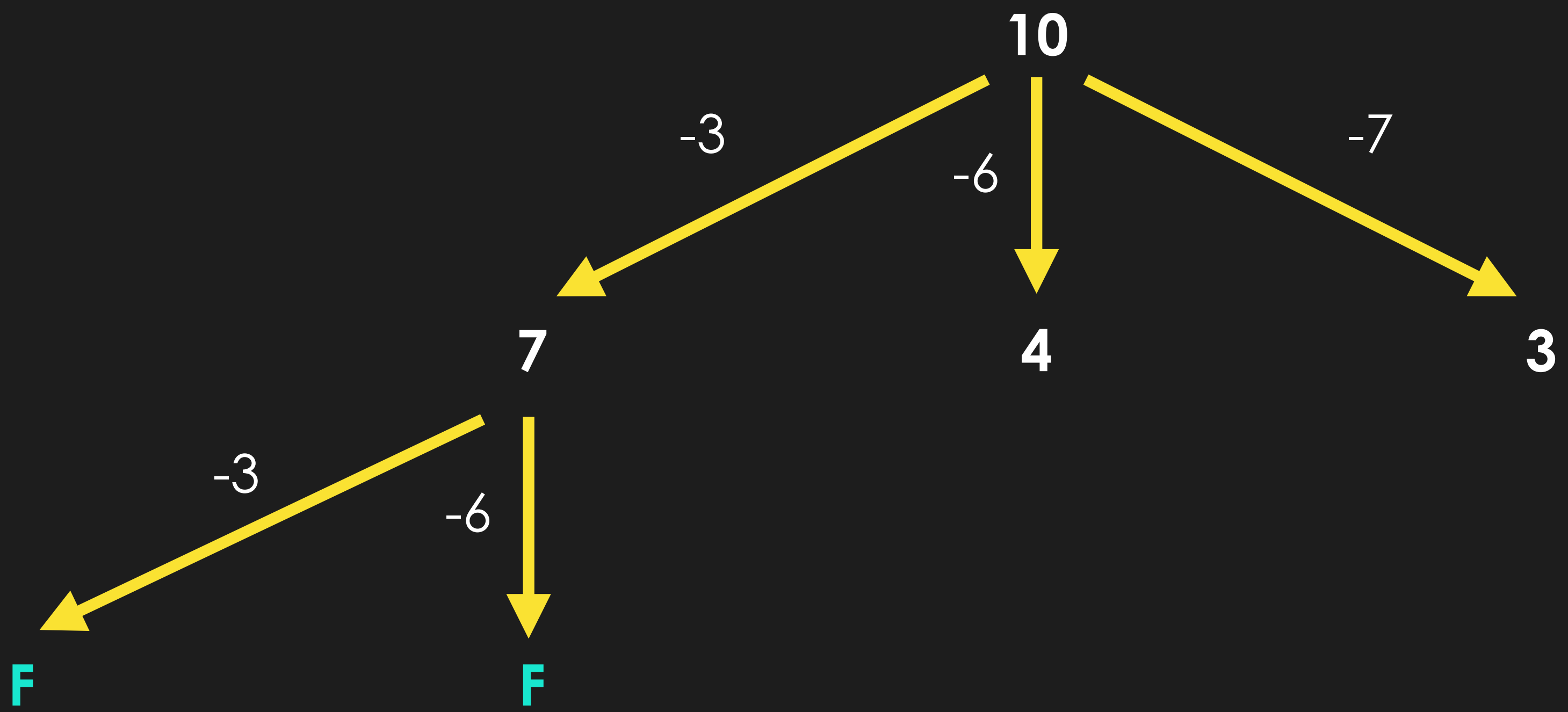
m	1	4	
memo	FALSE	FALSE	

CanSumMemo



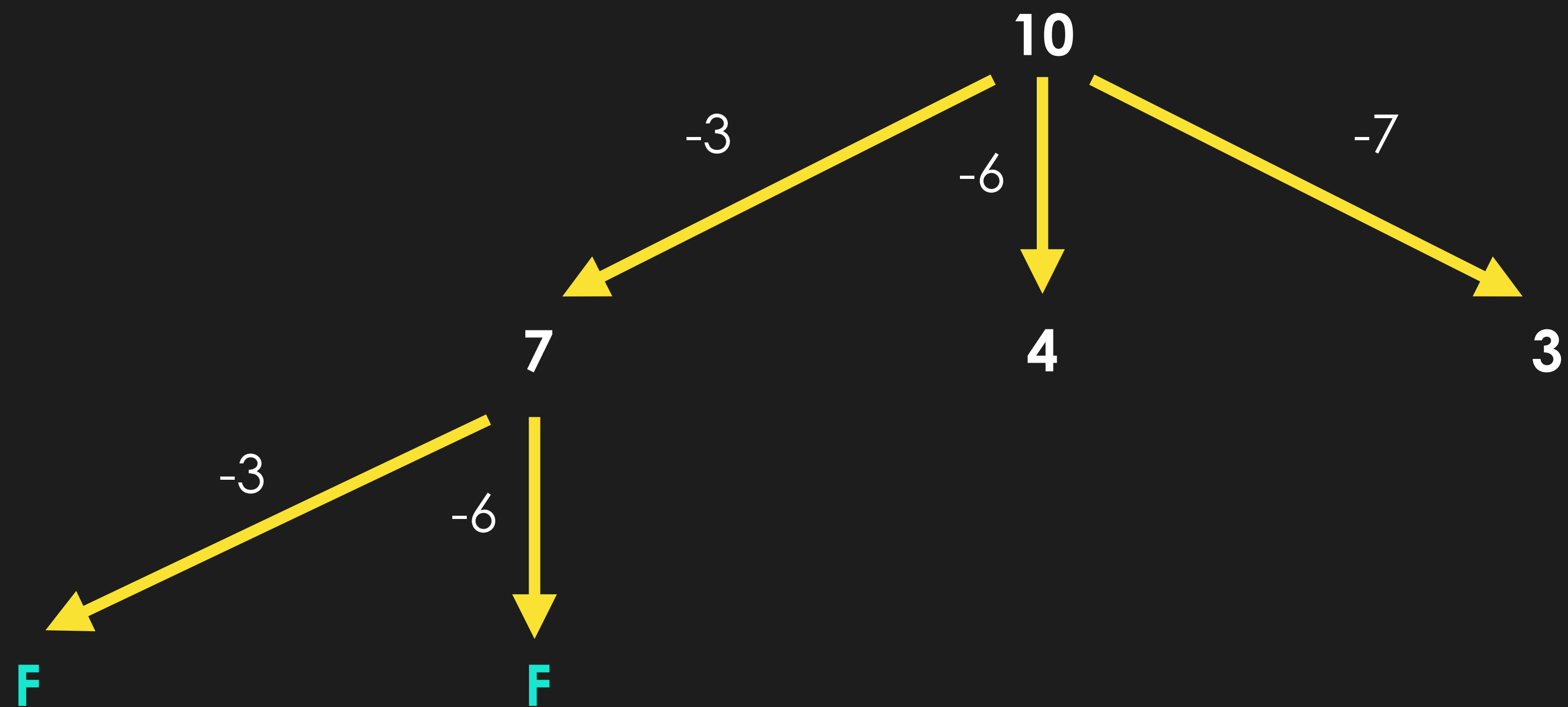
m	1	4	
memo	FALSE	FALSE	

CanSumMemo



m	1	4	
memo	FALSE	FALSE	

CanSumMemo



Time Complexity: $m * n$

Space Complexity: m

m	1	4	
memo	FALSE	FALSE	

CanSumMemo

```
def CanSum(array, target):  
    if target == 0:  
        return 1  
    if target < 0:  
        return 0  
  
    for i in array:  
        newTarget = target - i  
        if (CanSum(array, newTarget)):  
            return True  
  
    return False
```

DP Problem #4: Best String Construct

DP Problem #4: Best String Construct

Given a target string, and an array of strings, determine whether the array of strings **can be used to construct the target string**, returning the combination with the **least number of strings**

Example:

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]

target = "HOLLER"

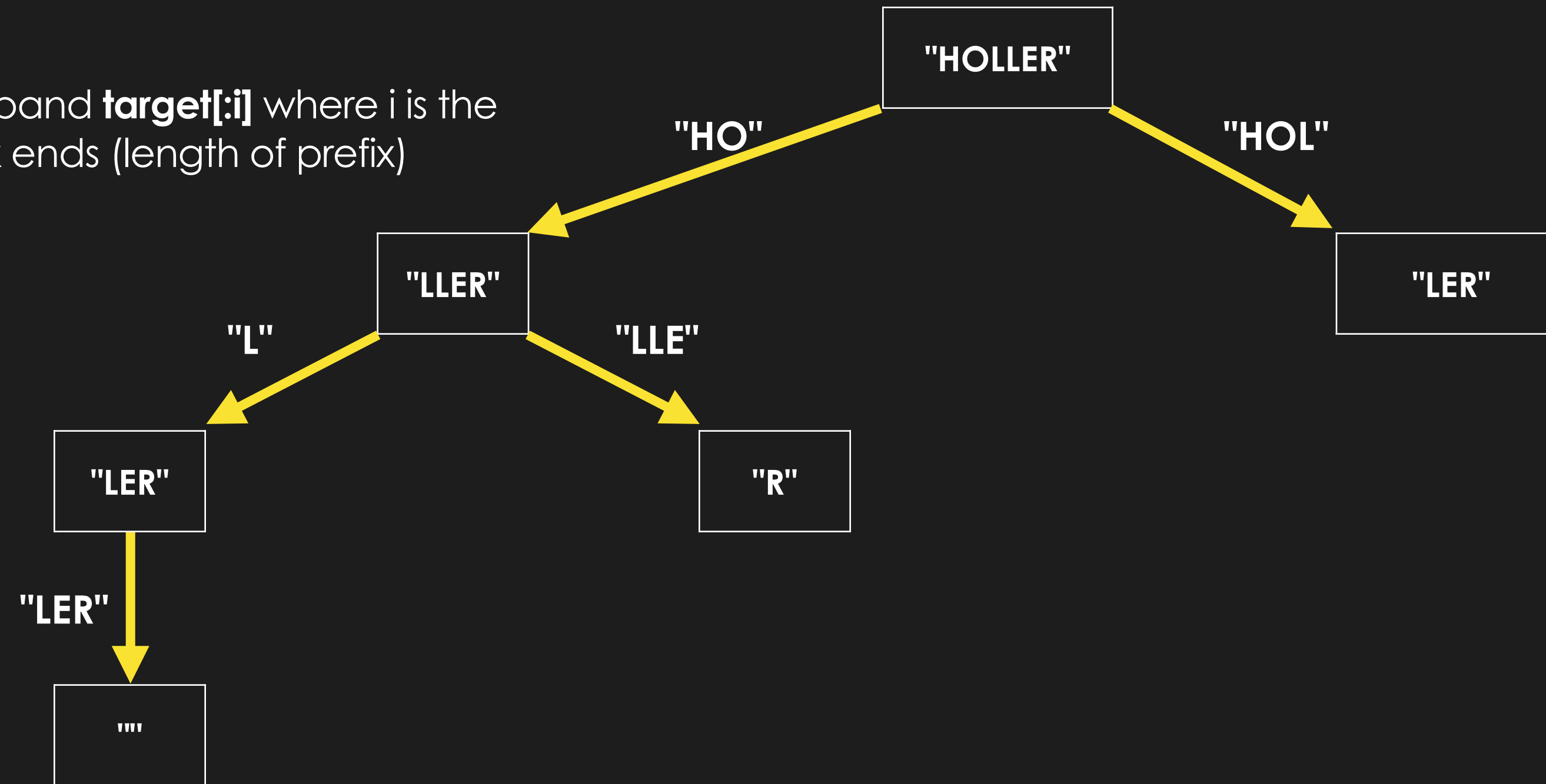
stringConstruct(array, target) => ["HOL", "LER"]

Note: ["HO", "LL", "ER"] is also an answer, but it is not the array with the least elements

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)

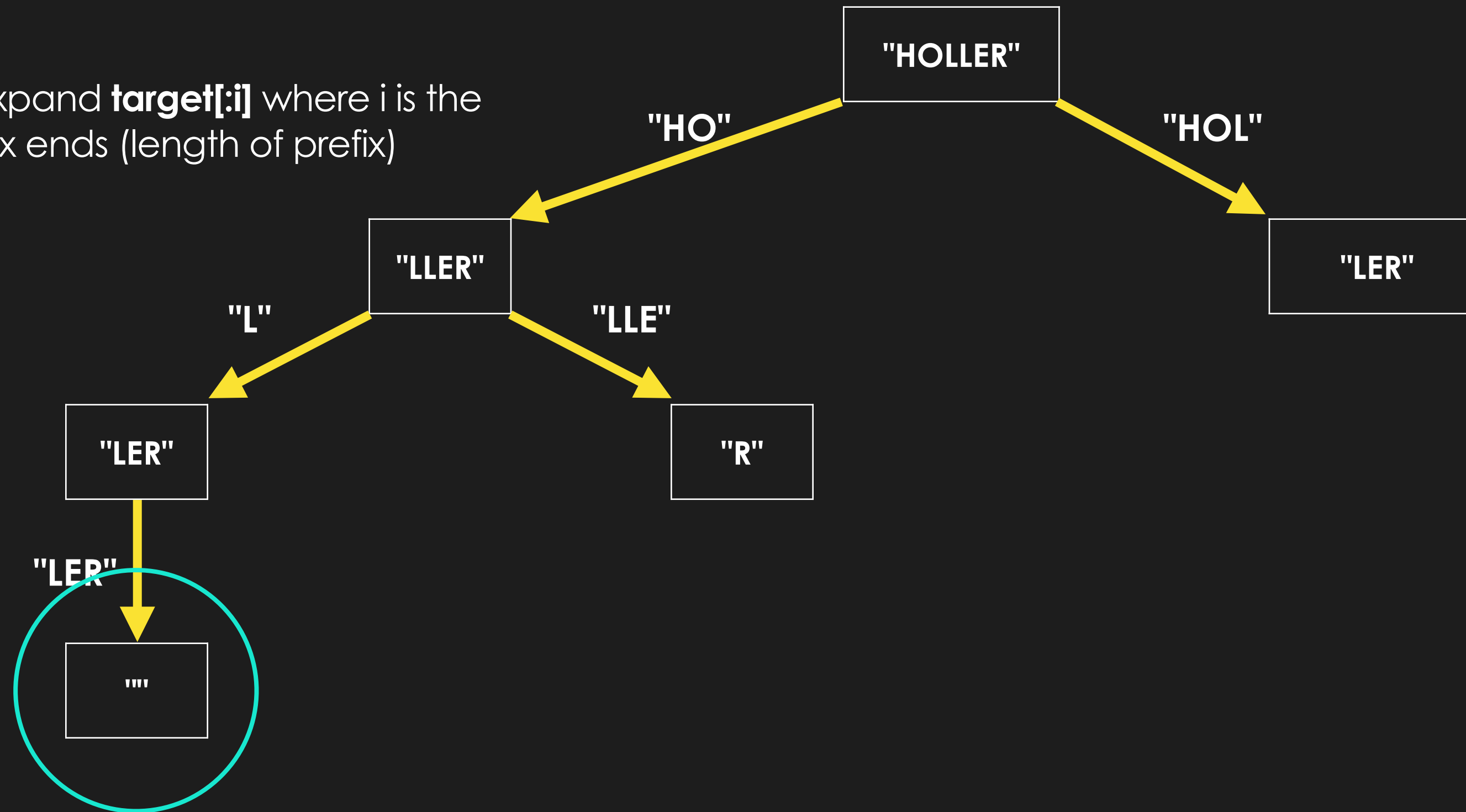


String Construct Optimal Substructure

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)



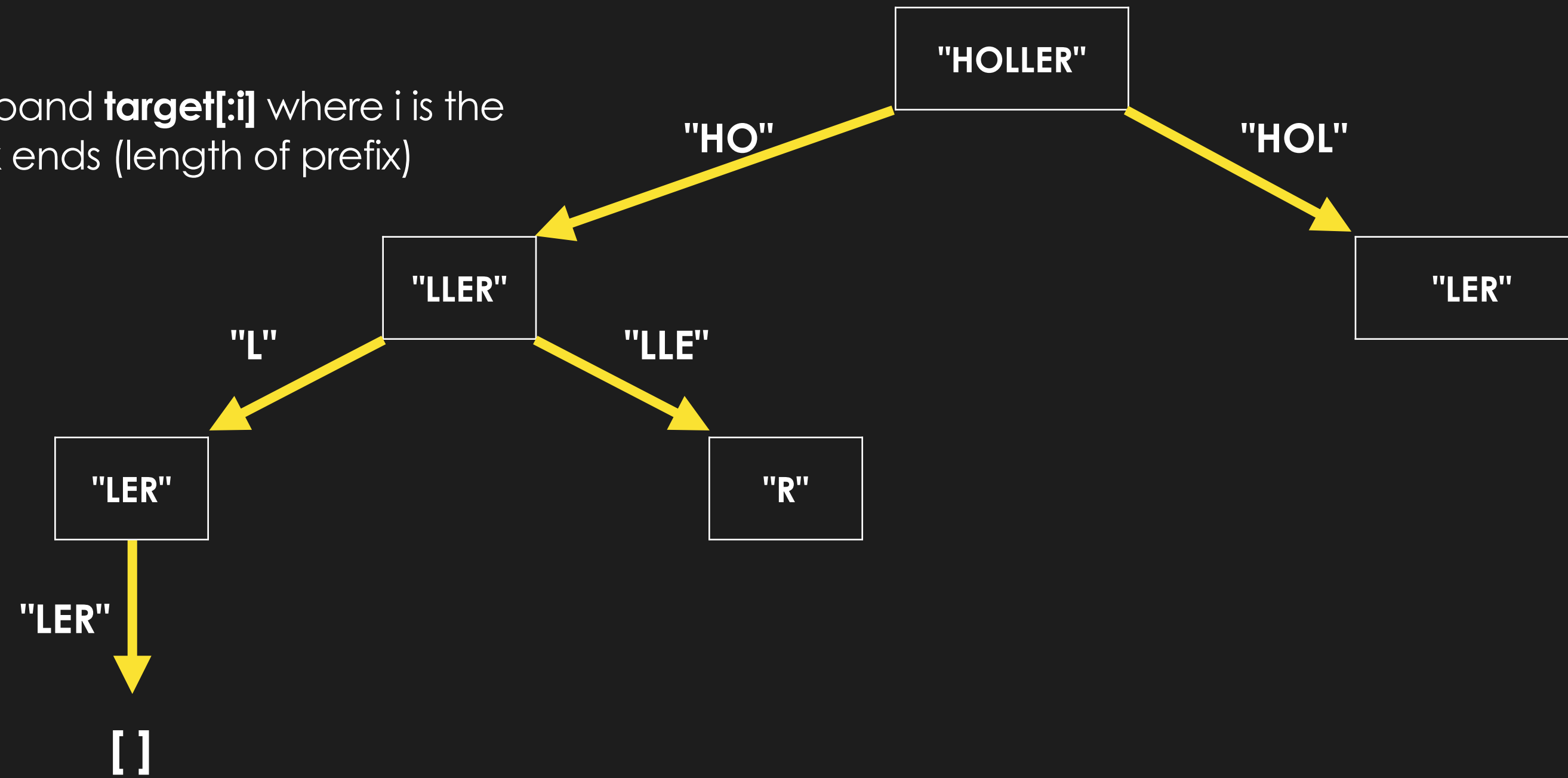
Base case 1: empty string (string can be constructed, return **empty array**)

String Construct Optimal Substructure

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)

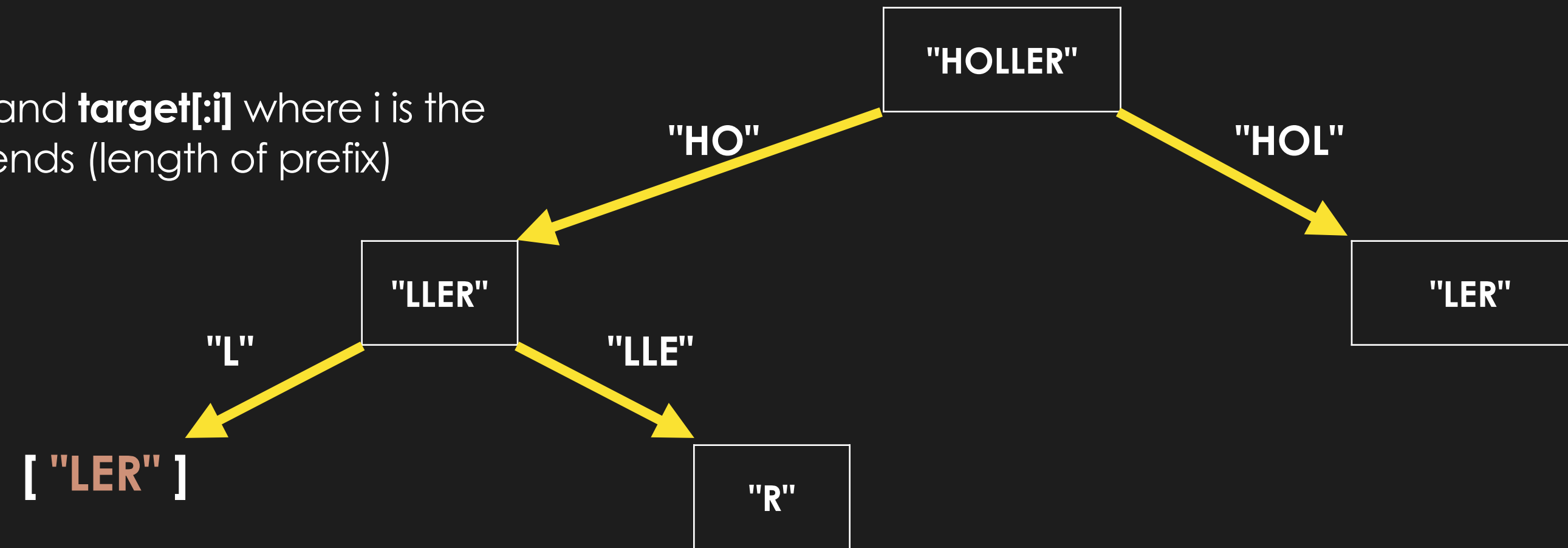


String Construct Optimal Substructure

```
array = [ "HO", "HOL", "L", "ER", "LER", "LLE" ]  
target = "HOLLER"
```

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)

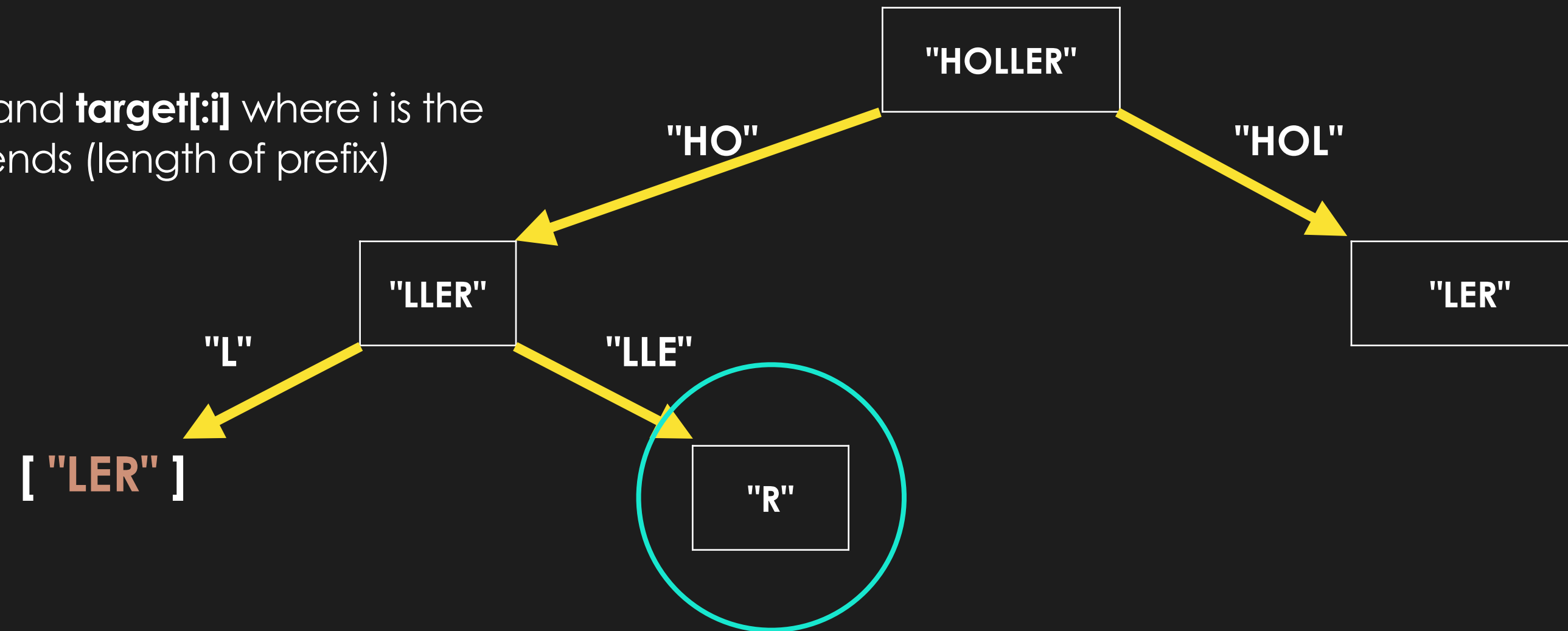


String Construct Optimal Substructure

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)



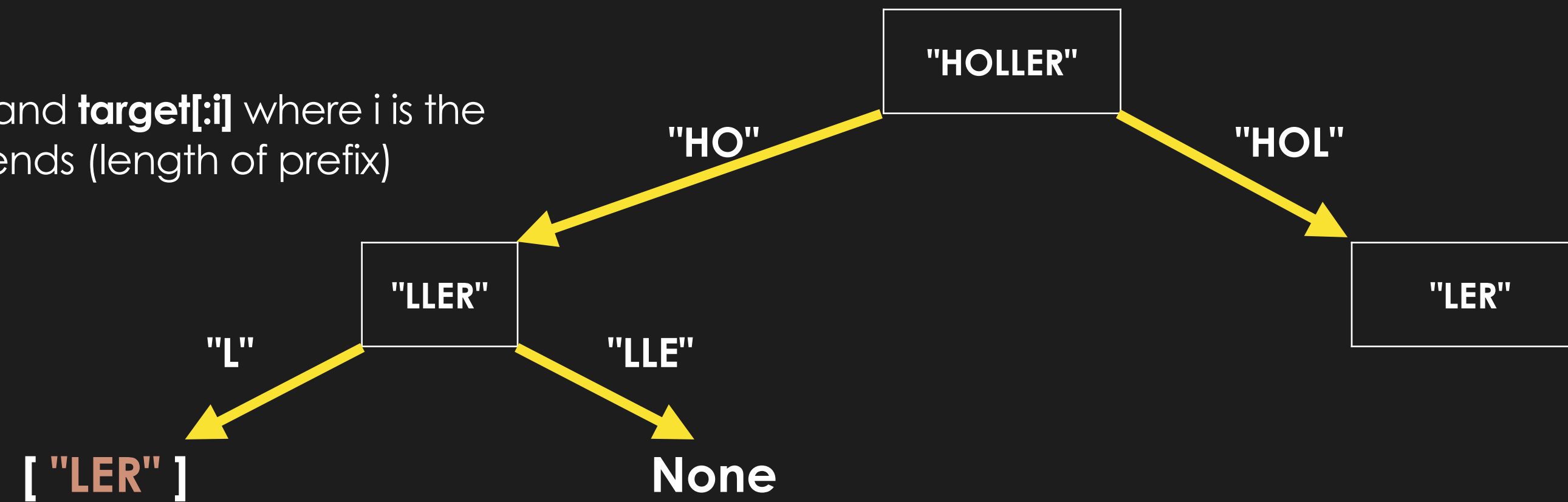
Base case 2: non-empty string (string cannot be constructed, return **None**)

String Construct Optimal Substructure

```
array = [ "HO", "HOL", "L", "ER", "LER", "LLE" ]  
target = "HOLLER"
```

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)

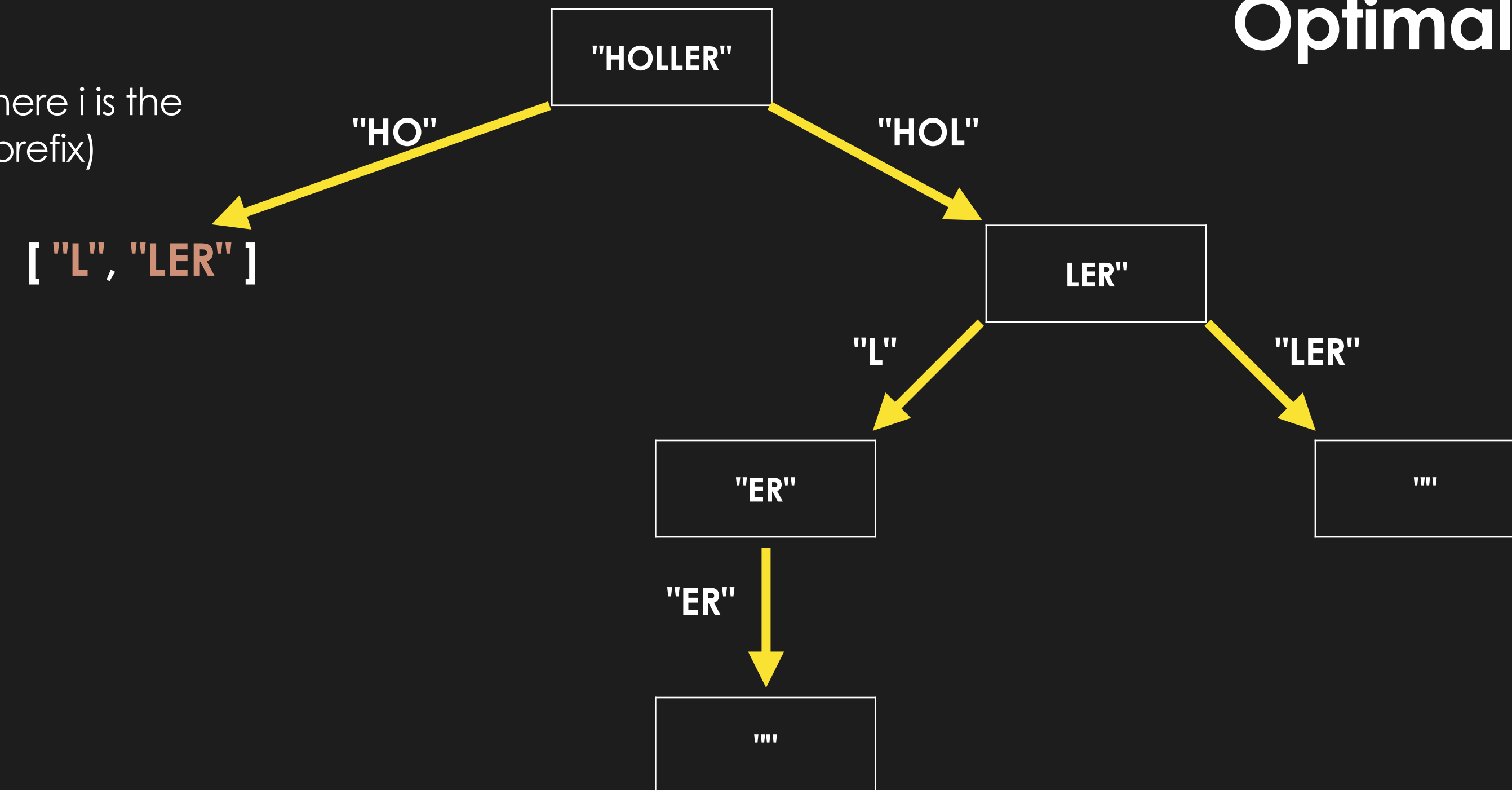


String Construct Optimal Substructure

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)

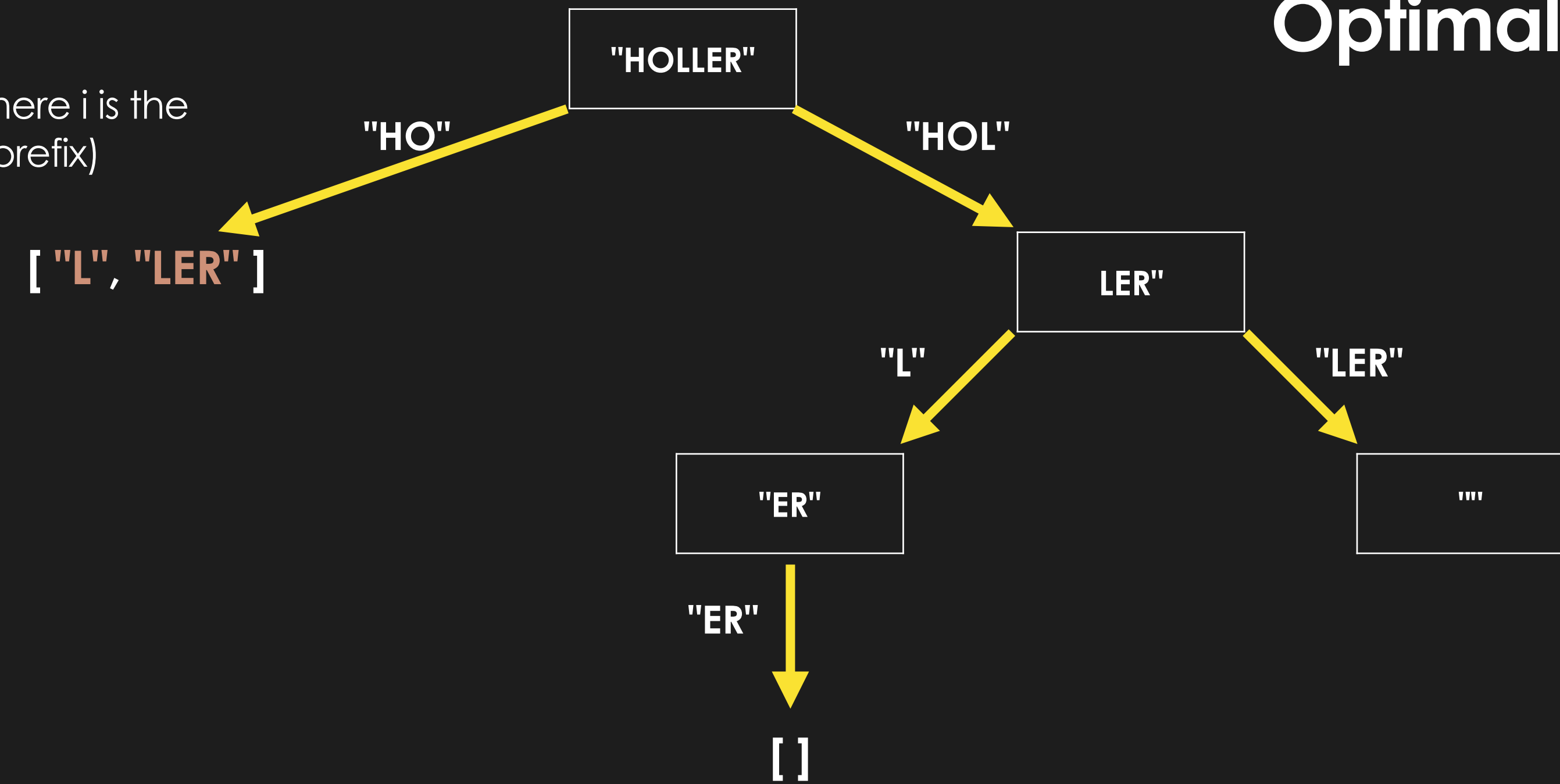


String Construct Optimal Substructure

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)

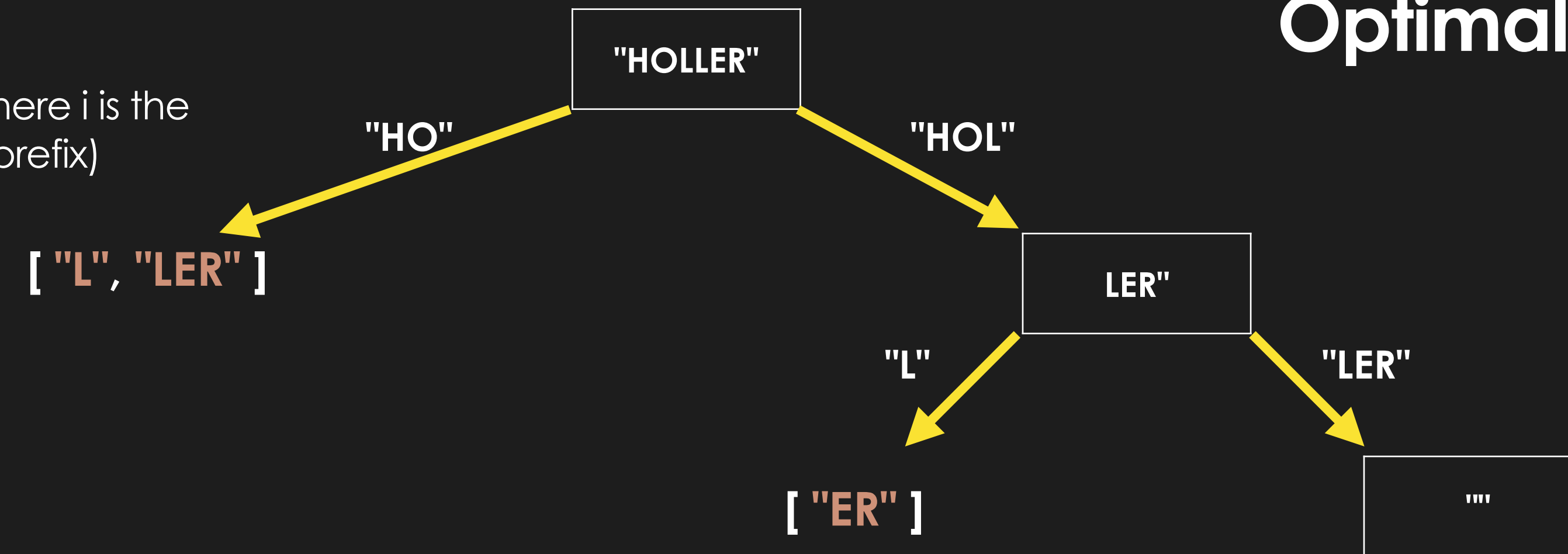


String Construct Optimal Substructure

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)

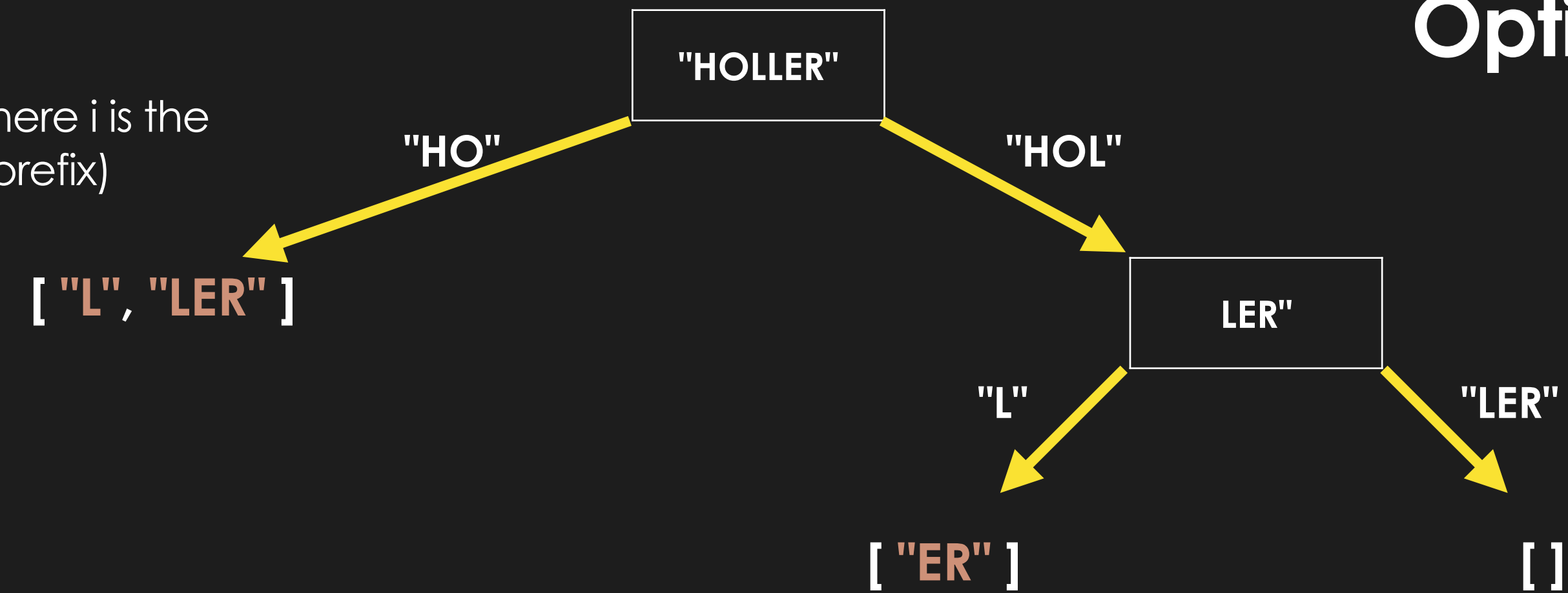


String Construct Optimal Substructure

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)

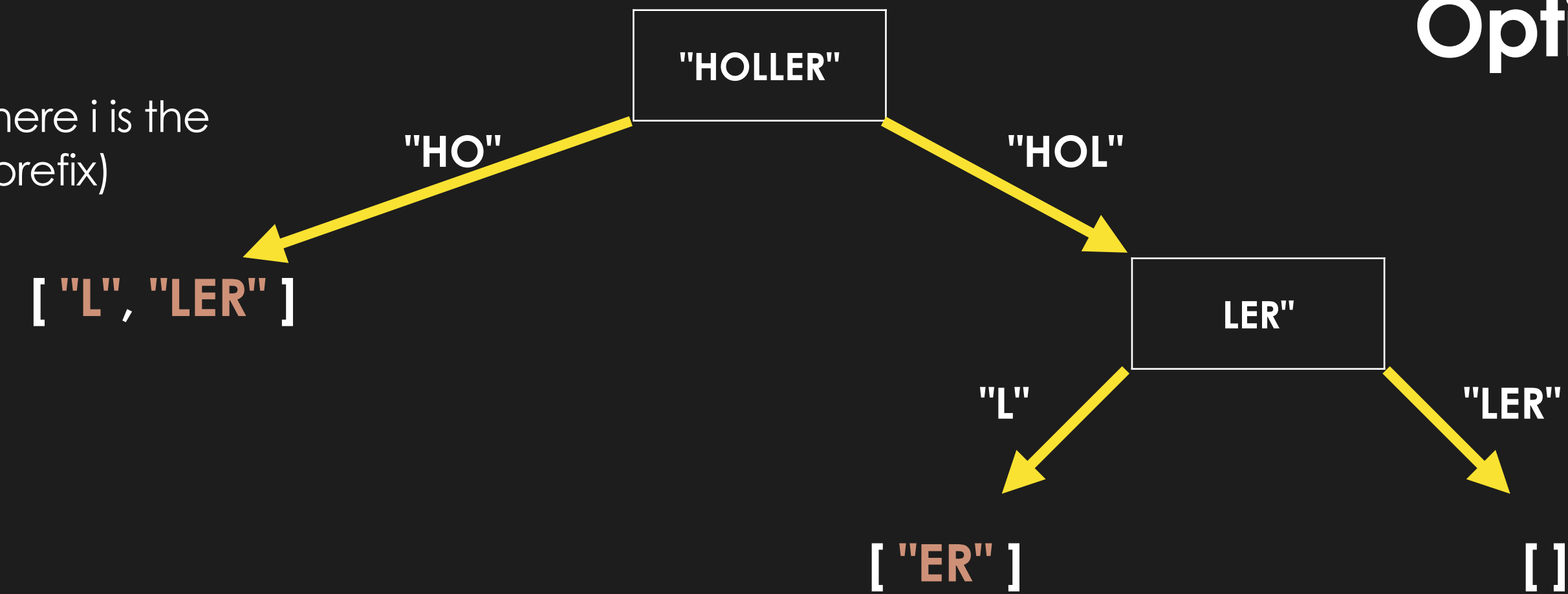


String Construct Optimal Substructure

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)



String Construct

Optimal Substructure

Since right path has lesser elements in returning array, use that

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

Recursive pattern:

If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)



String Construct Optimal Substructure

```
array = [ "HO", "HOL", "L", "ER", "LER", "LLE" ]  
target = "HOLLER"
```

Recursive pattern:

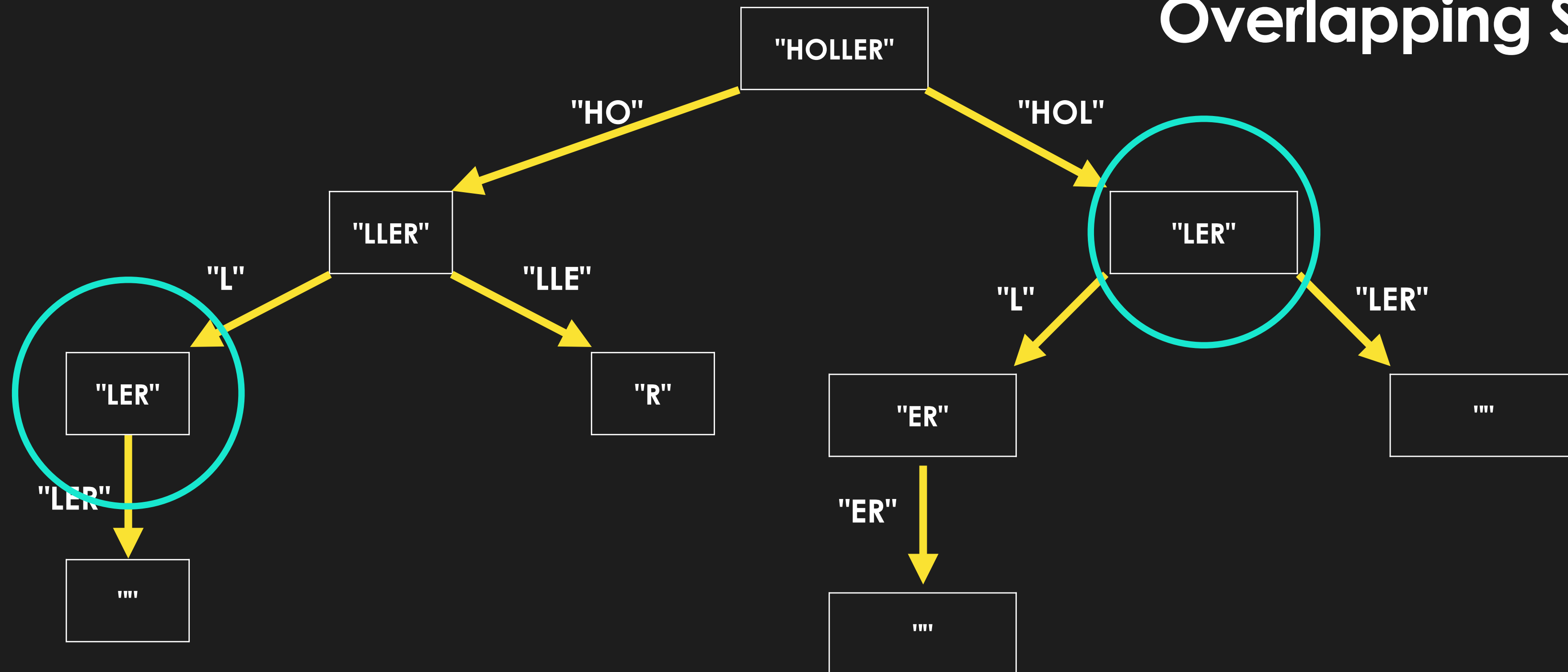
If prefix exists in array, expand **target[:i]** where i is the index at which the prefix ends (length of prefix)

["HOLLER"]

String Construct Optimal Substructure

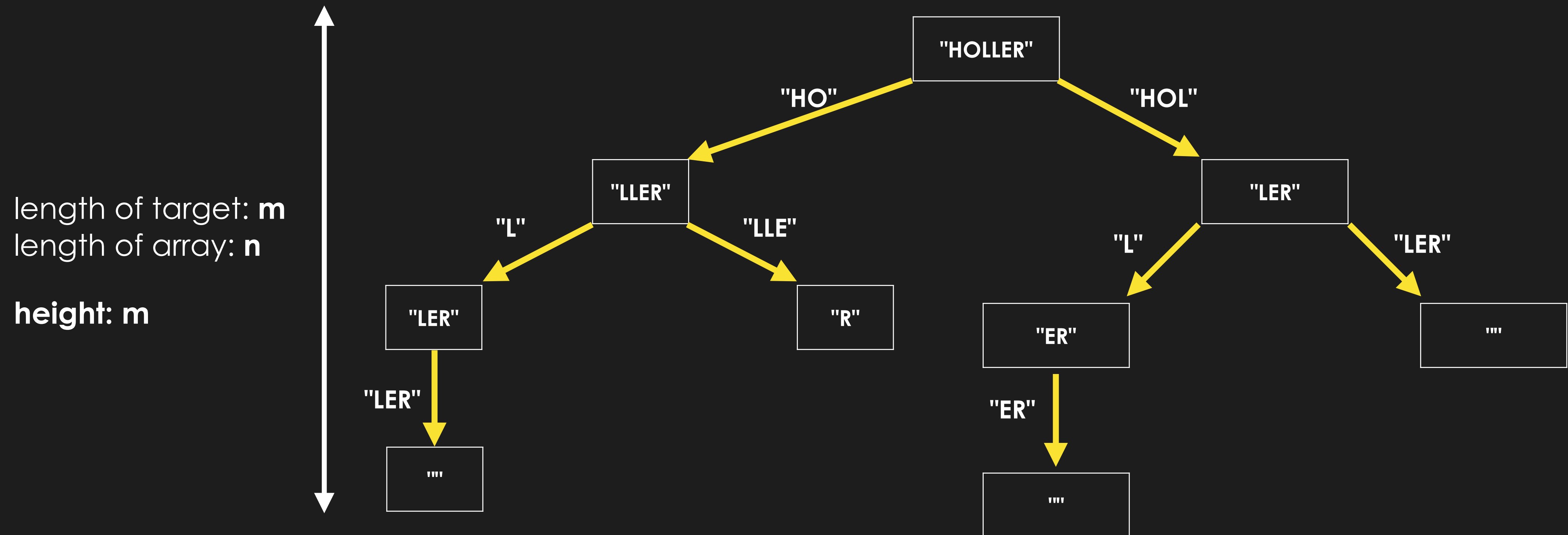
array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

String Construct Overlapping Subproblems



array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

String Construct Overlapping Subproblems



Implementation of string construct

```
def stringConstruct(array, string):  
    if string == "":  
        return []  
  
    bestRes = None  
    for str in array:  
        i = string.find(str)  
  
        if i != 0:  
            continue  
  
        res = stringConstruct(array, string[len(str):])  
        if res != None:  
            if bestRes == None or len(bestRes) > len(res):  
                bestRes = res  
                bestRes.insert(0, str)  
  
    return bestRes
```

```

def stringConstruct(array, string):
    if string == '':
        return []

    bestRes = None
    for str in array:
        i = string.find(str)

        if i != 0:
            continue

        res = stringConstruct(array, string[len(str):])
        if res != None:
            if bestRes == None or len(bestRes) > len(res):
                bestRes = res.copy()
                bestRes.insert(0, str)

    return bestRes

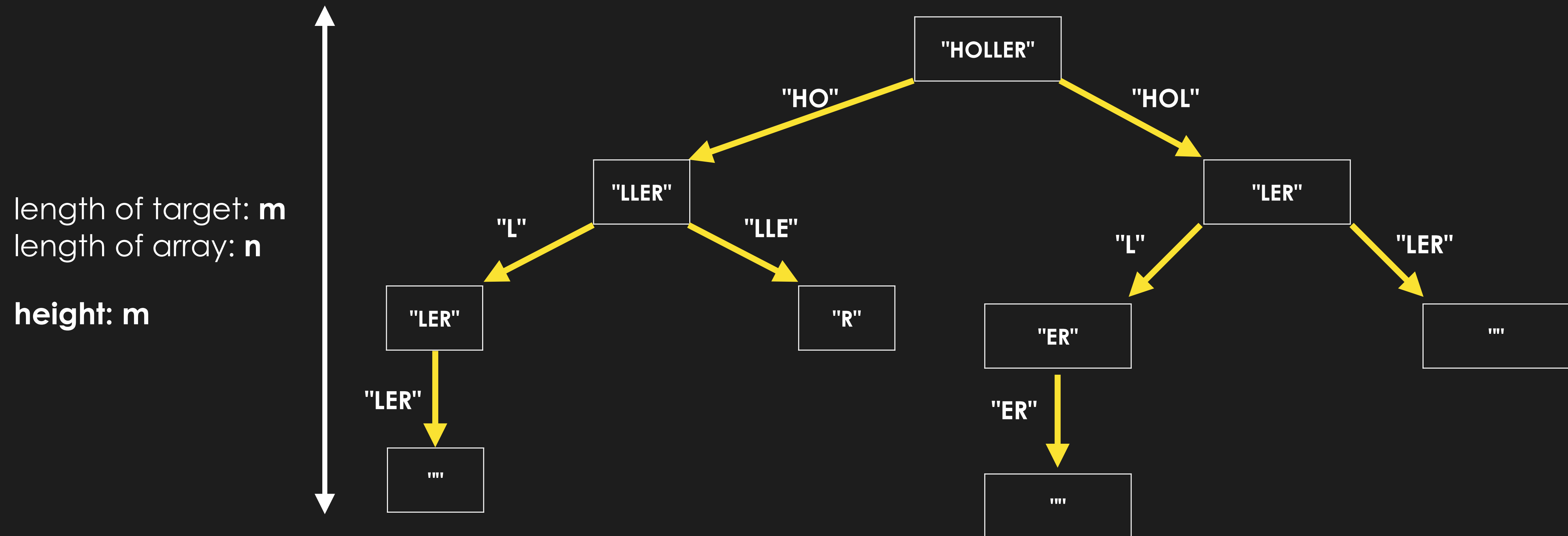
```

Diagram illustrating the recursive process with complexity annotations:

- Annotation **n** with an arrow pointing to the `for str in array:` loop.
- Annotation **m** with an arrow pointing to the `string.find(str)` operation.
- Annotation **n^m** with an arrow pointing to the recursive call `stringConstruct(array, string[len(str):])`.

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

String Construct Overlapping Substructure



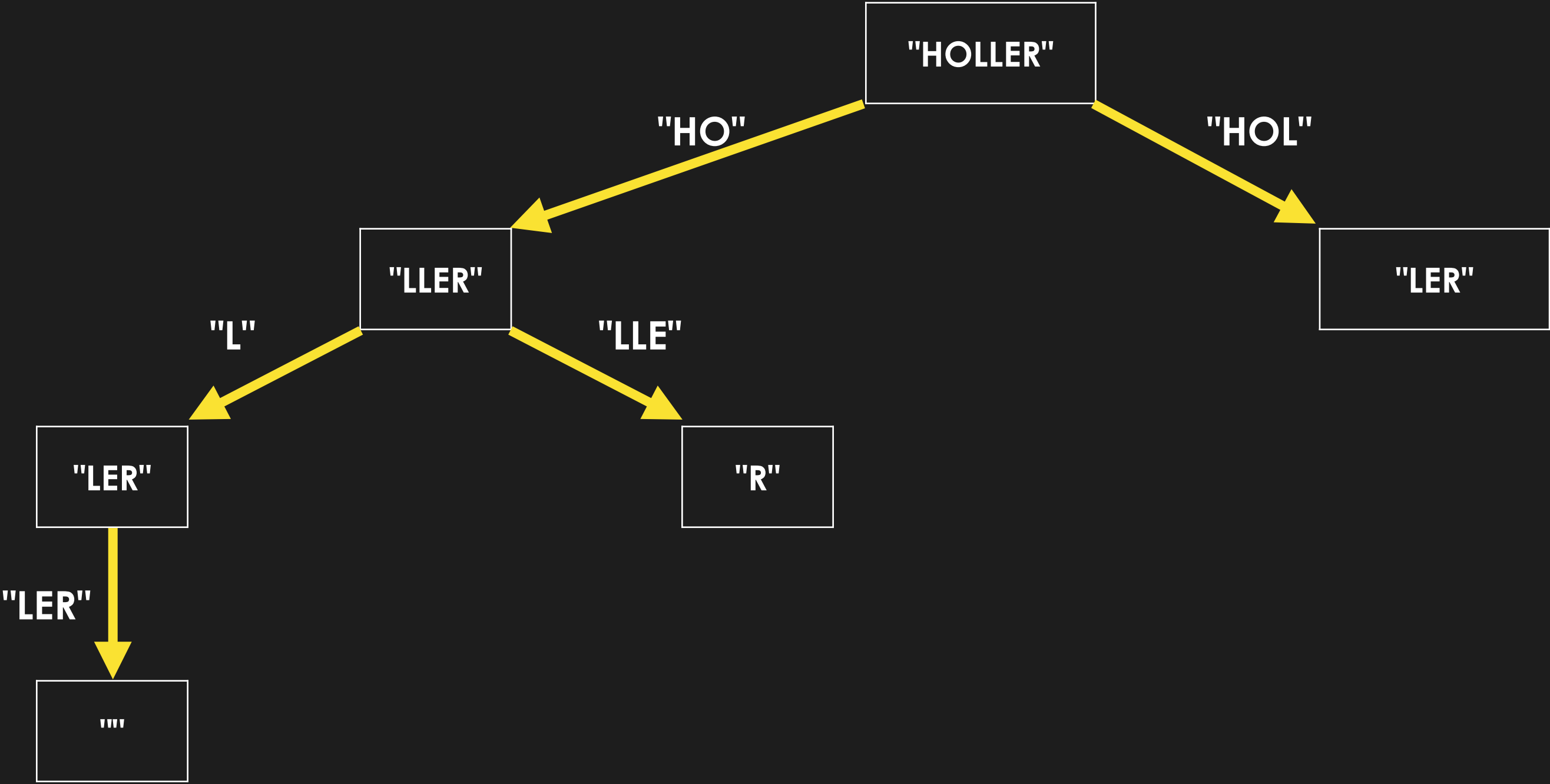
time complexity: $m * n^{2m}$

space complexity: m

Memoization

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

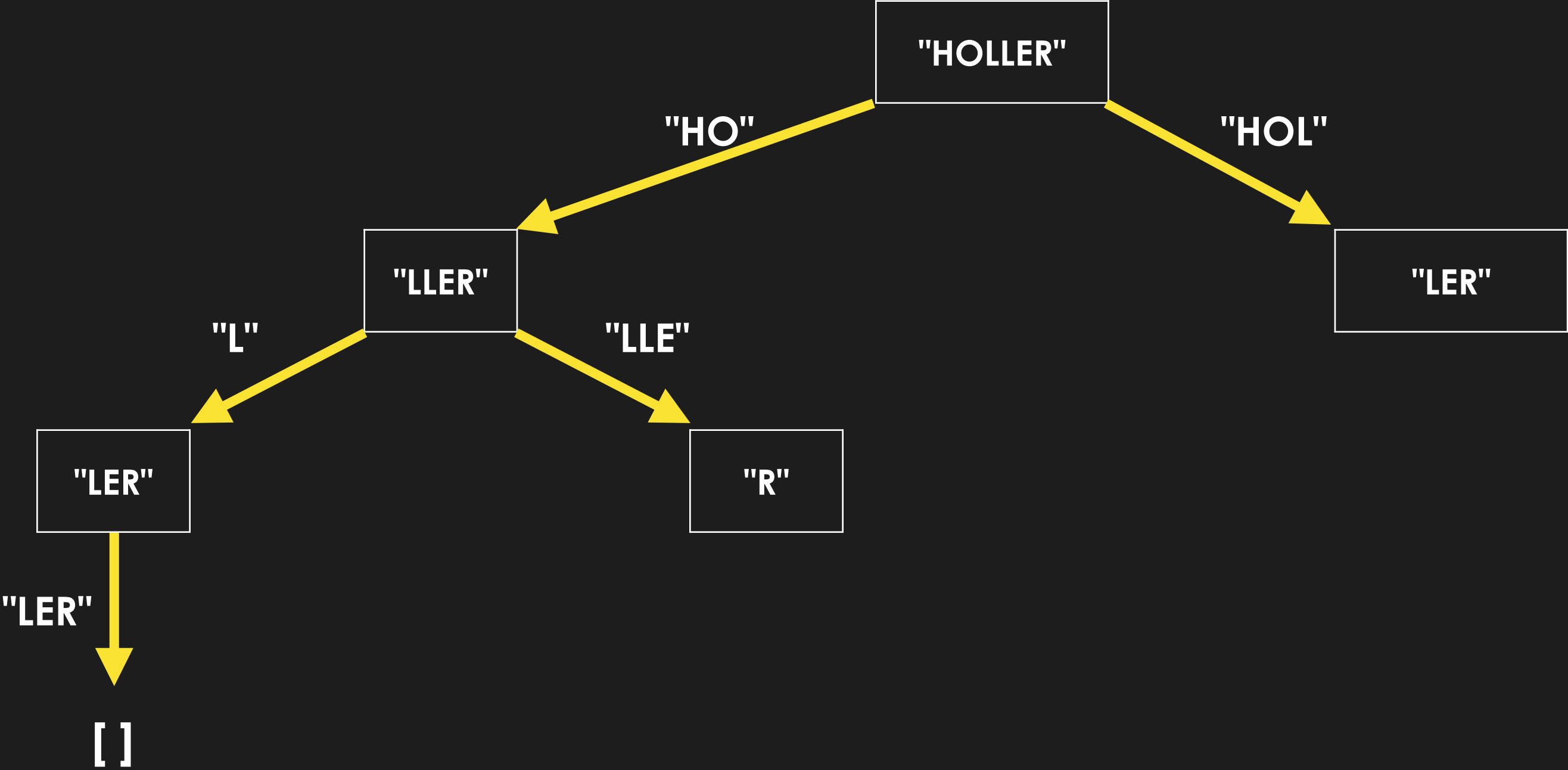
String Construct Optimal Substructure



str						
mem						

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

String Construct Optimal Substructure

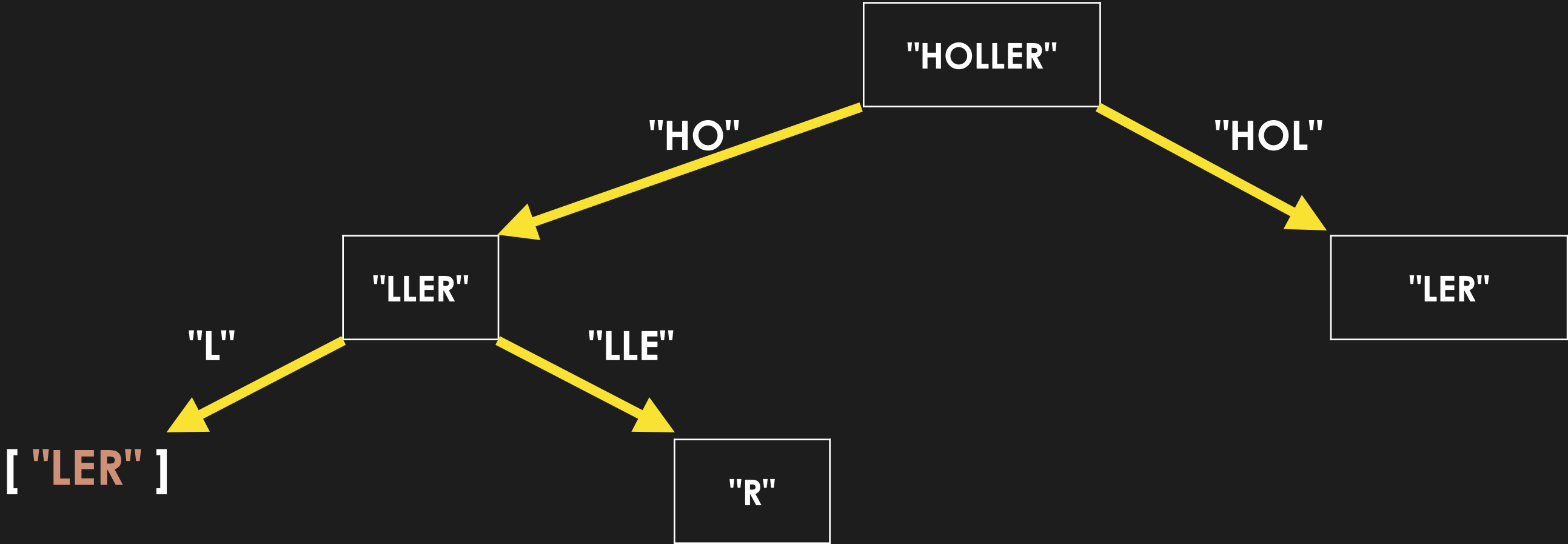


str						
mem						

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

String Construct

Optimal Substructure

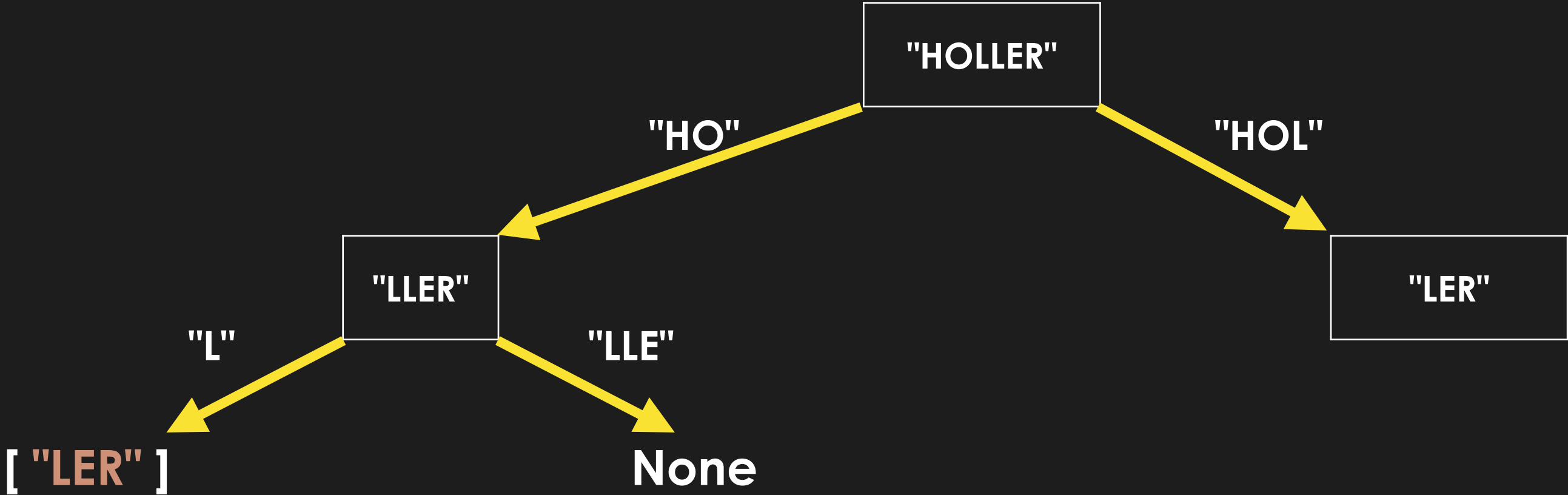


str	"LER"					
mem	["LER"]					

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

String Construct

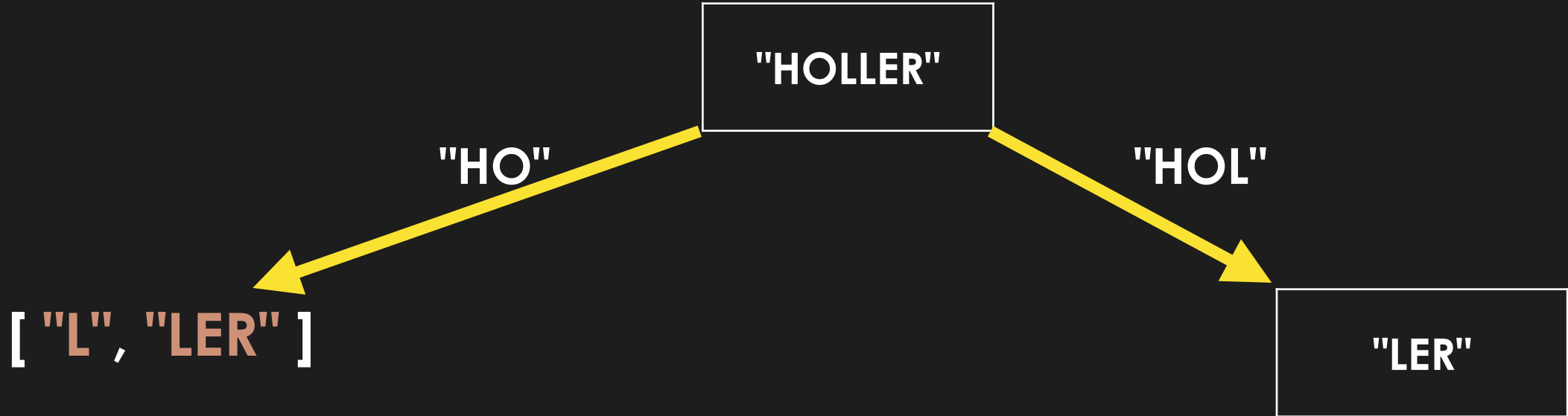
Optimal Substructure



str	"LER"					
mem	["LER"]					

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

String Construct Optimal Substructure

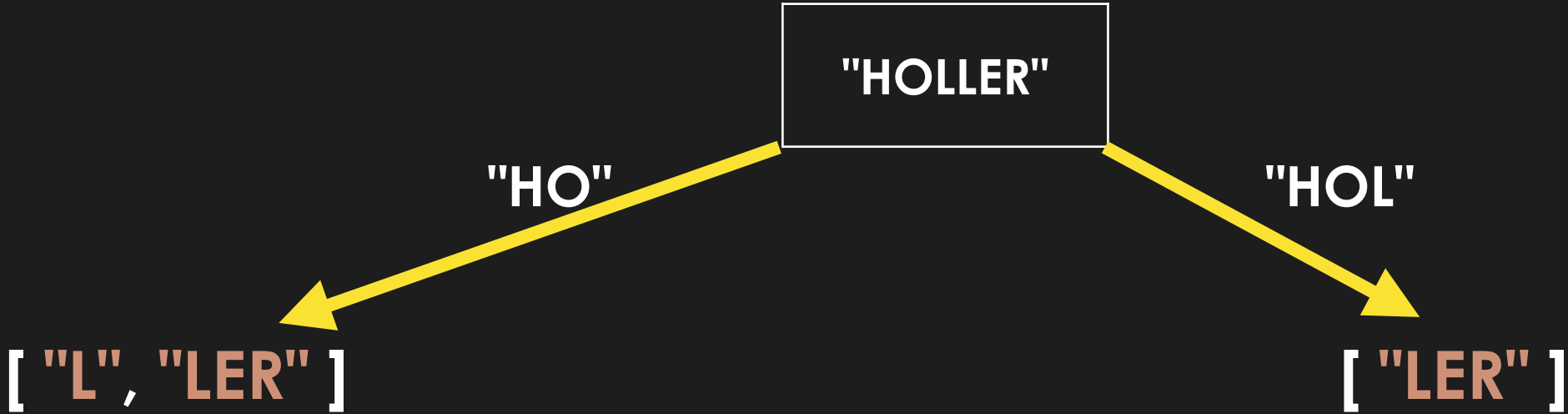


str	"LER"	"LLER"				
mem	["LER"]	["L", LER]				

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

String Construct

Optimal Substructure



str	"LER"	"LLER"				
mem	["LER"]	["L", LER"]				

Implementation of string construct memo

```

memo = {}

def stringConstruct(array, string):
    if string in memo:
        return memo[string]

    if string == "":
        return []

    bestRes = None

    for str in array:
        i = string.find(str)

        if i != 0:
            continue

        res = stringConstruct(array, string[len(str):])
        if res != None:
            if bestRes == None or len(bestRes) > len(res):
                bestRes = res.copy()
                bestRes.insert(0, str)

    memo[string] = bestRes

    return bestRes

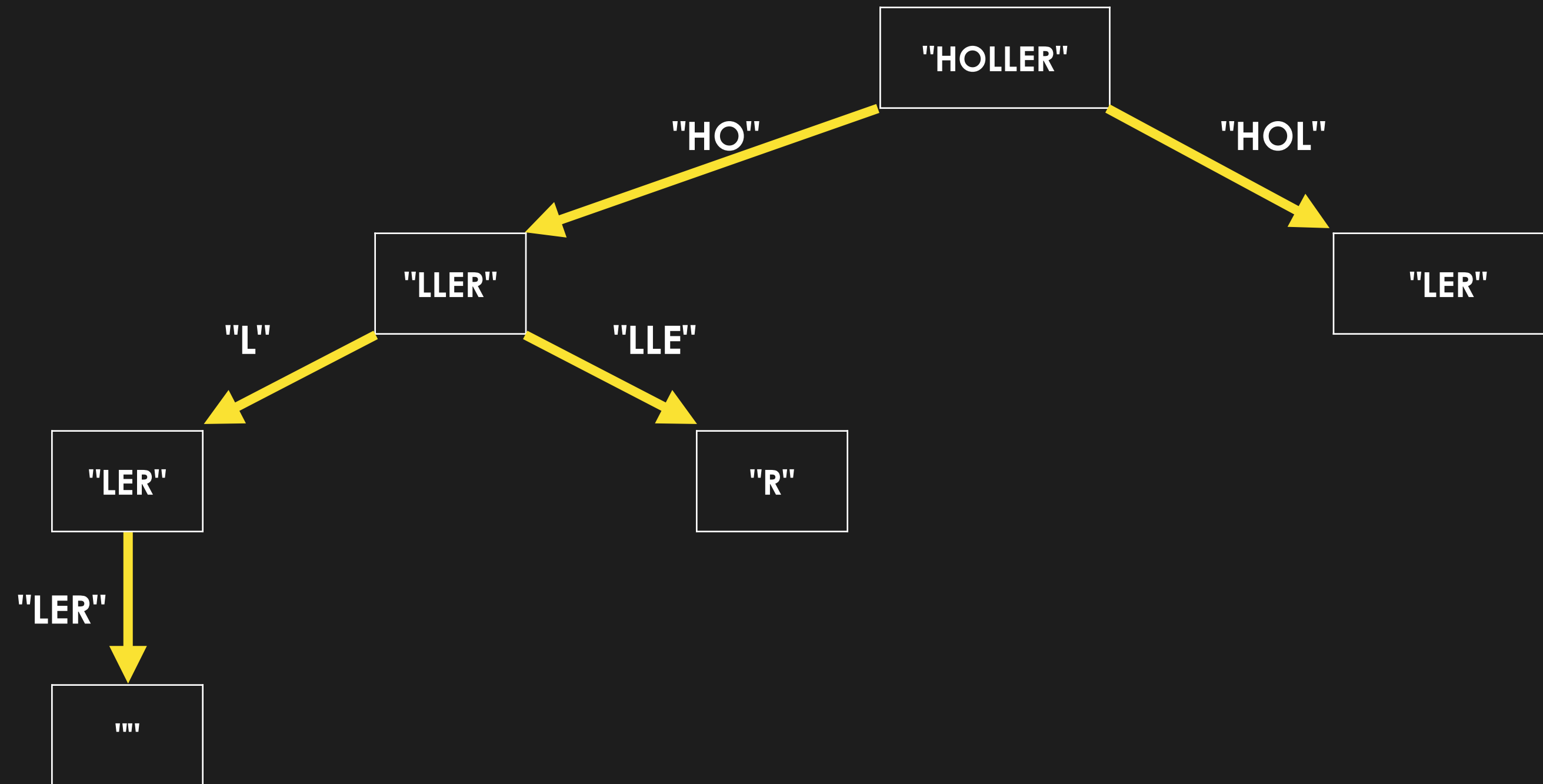
```

Diagram illustrating the recursive call and return flow in the `stringConstruct` function:

- n** (pink) and **m** (pink) are placed above the recursive call `stringConstruct(array, string[len(str):])` and the `return` statement, respectively. A pink arrow points from **n** to the recursive call, and another pink arrow points from **m** to the `return` statement.
- m** (yellow) is placed to the right of the recursive call. A yellow arrow points from **m** to the recursive call.

array = ["HO", "HOL", "L", "ER", "LER", "LLE"]
target = "HOLLER"

String Construct Optimal Substructure



time complexity: $m^2 * n$

space complexity: m

DP Problem #5: Longest Common Subsequence

DP Problem #5: Common Subsequences

Given two strings, find the longest subsequence present in both strings

DP Problem #5: Longest Common Subsequence

Given two strings, find the longest subsequence present in both strings

Example:

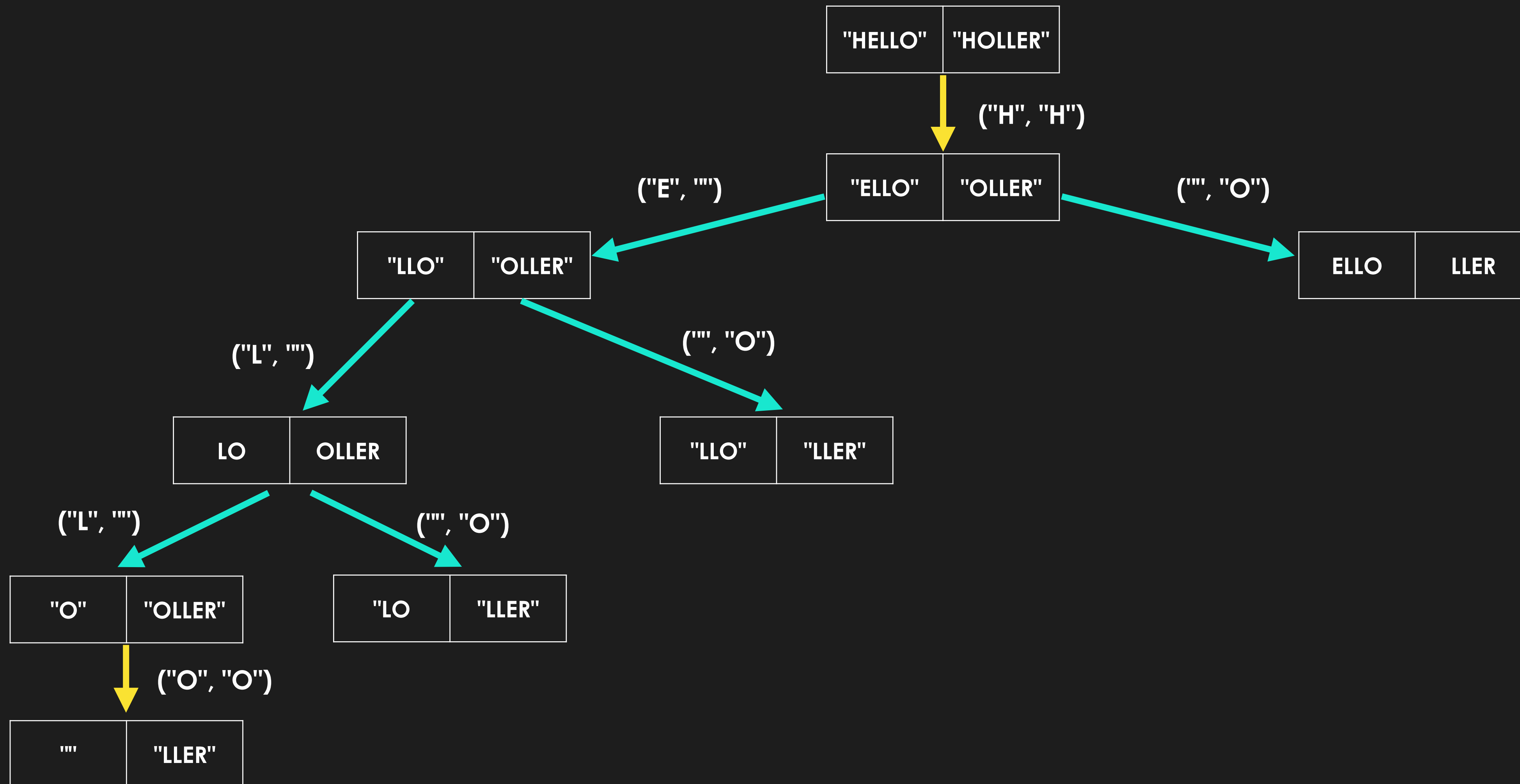
string1 = "HELLO"
string2 = "HOLLER"

lcs(string1, string2) => "HLL"

What do you think the
optimal substructure is?

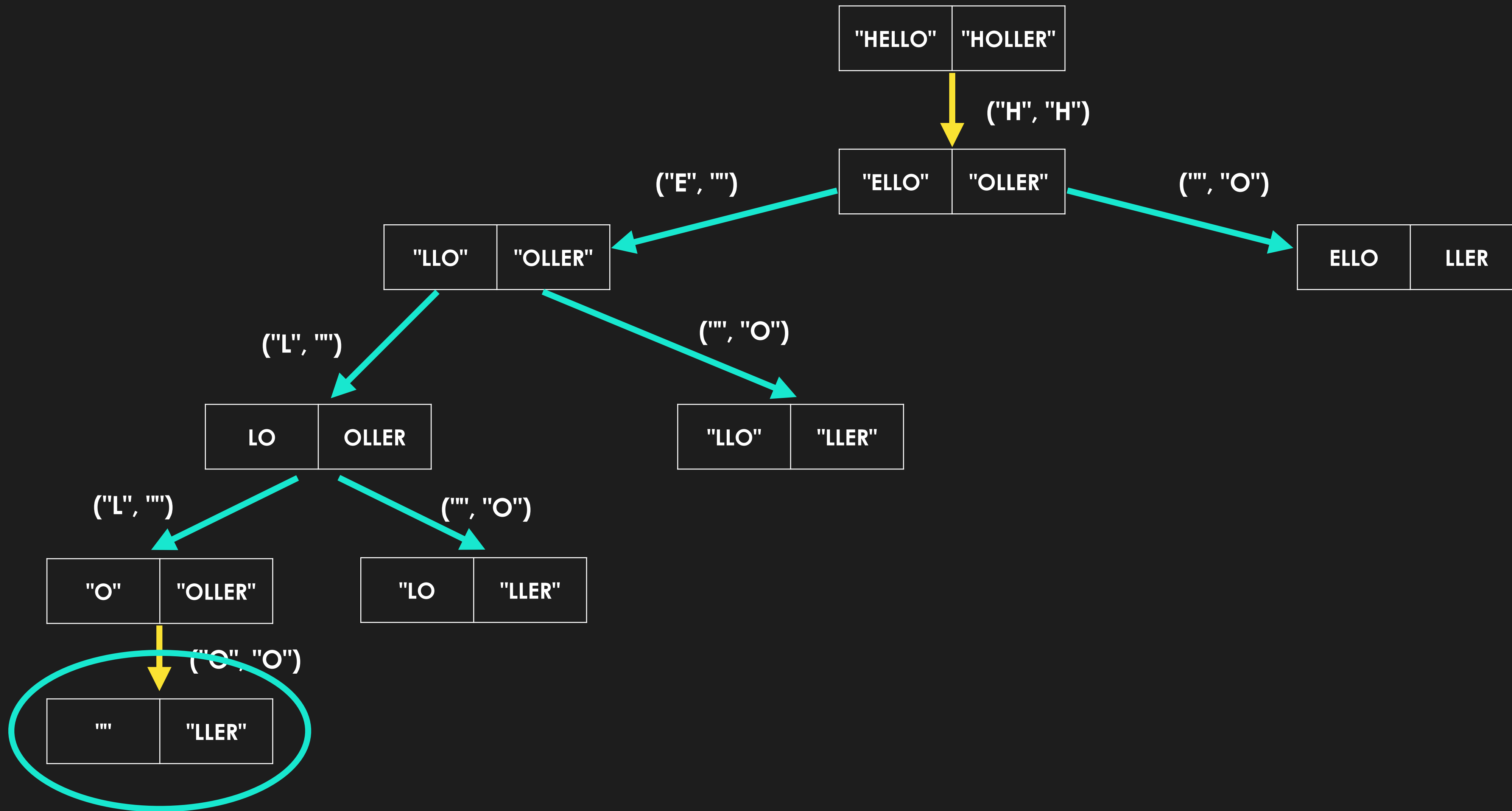
- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure



- **case 1:** first char matches
- **case 2:** first char doesn't match

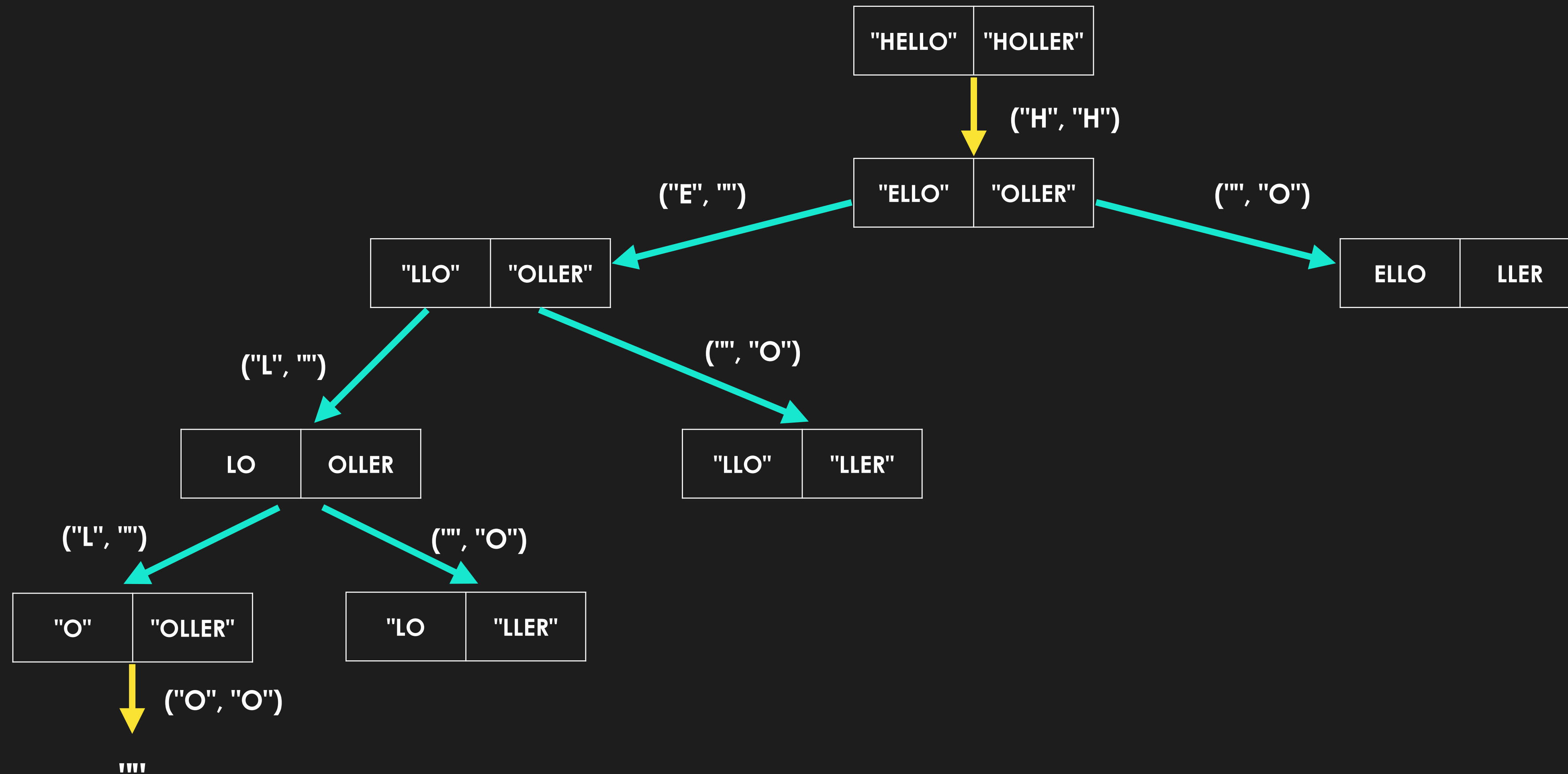
LCS Optimal Substructure



Base case!

- **case 1:** first char matches
- **case 2:** first char doesn't match

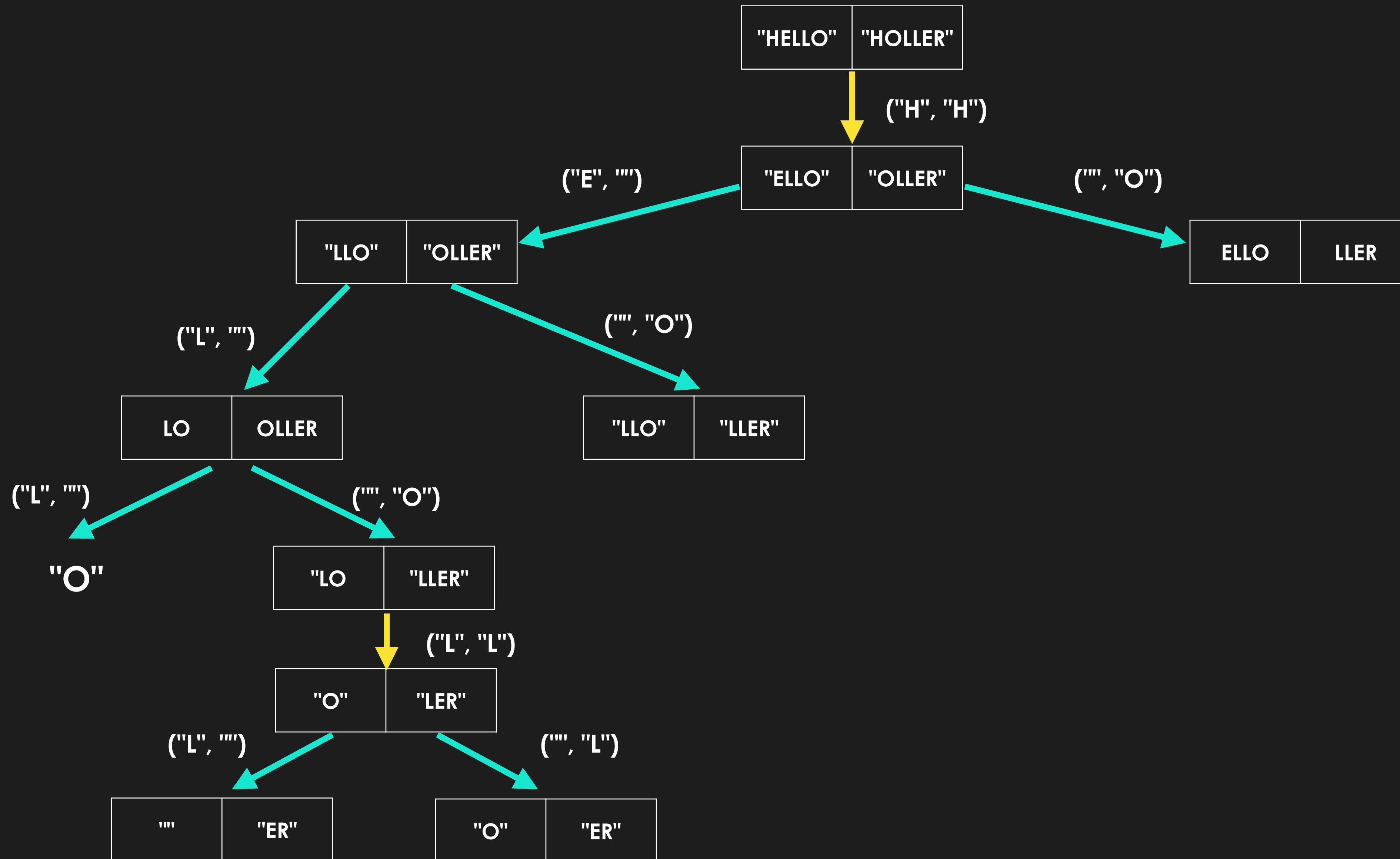
LCS Optimal Substructure



Base case!

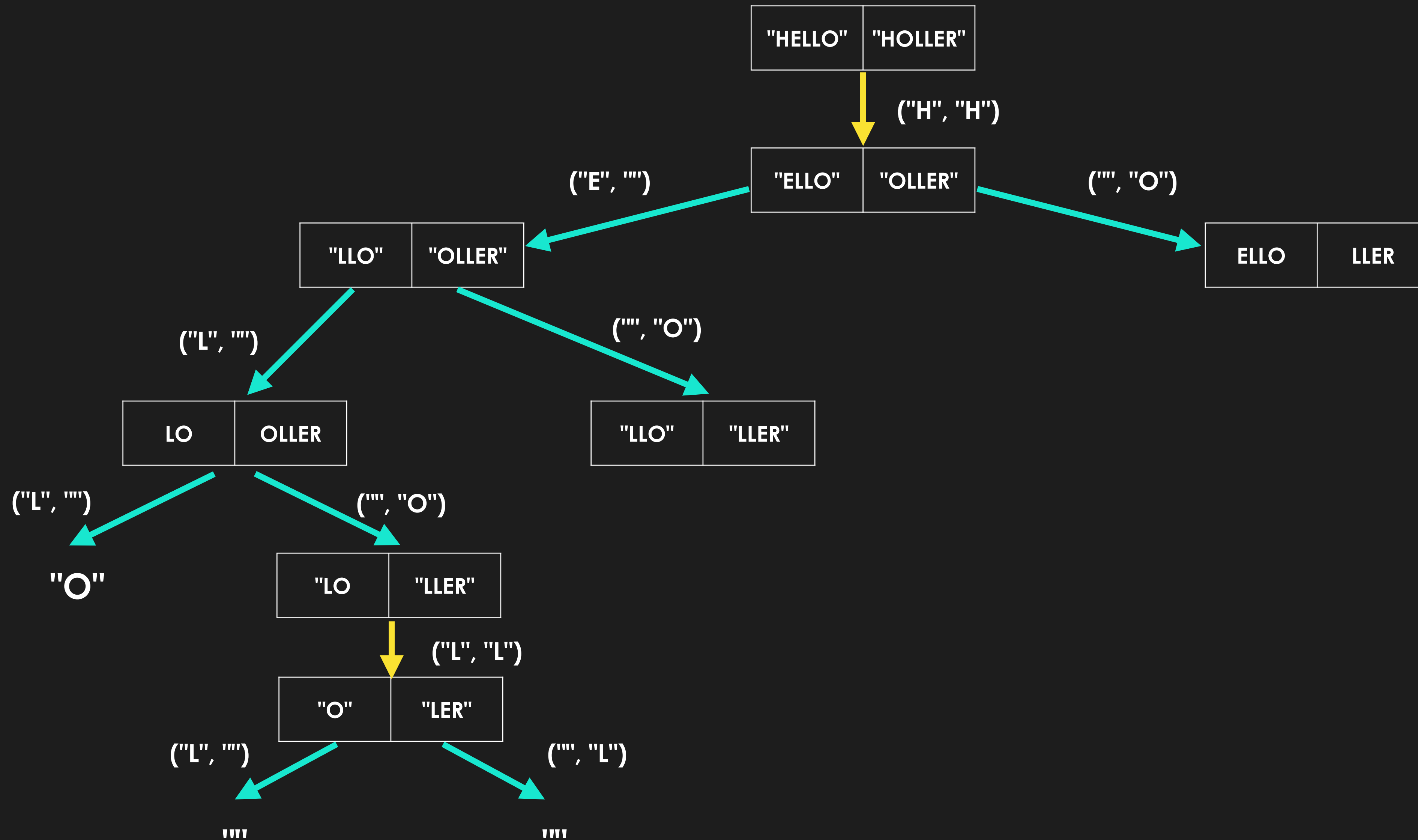
- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure



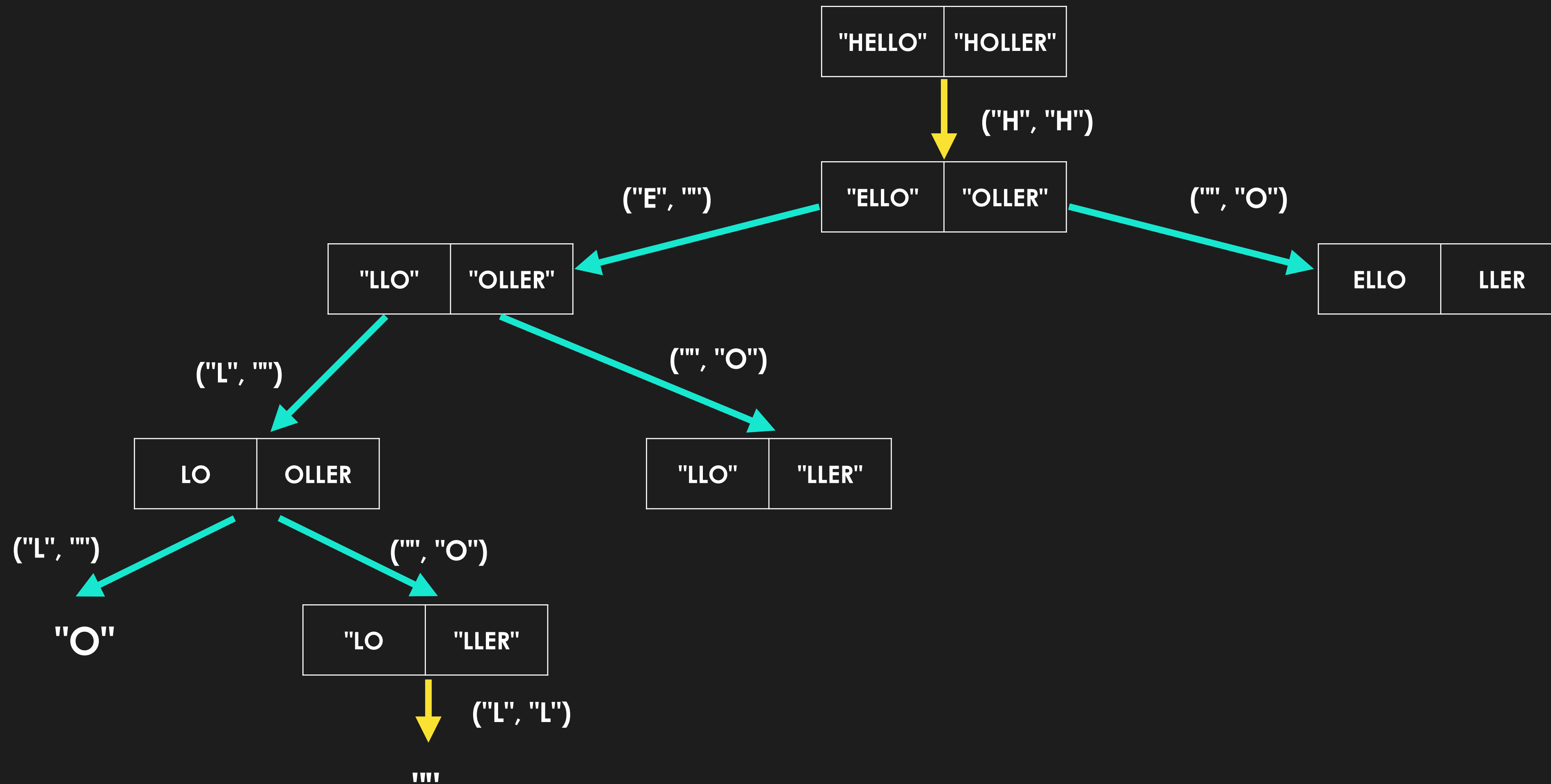
- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure



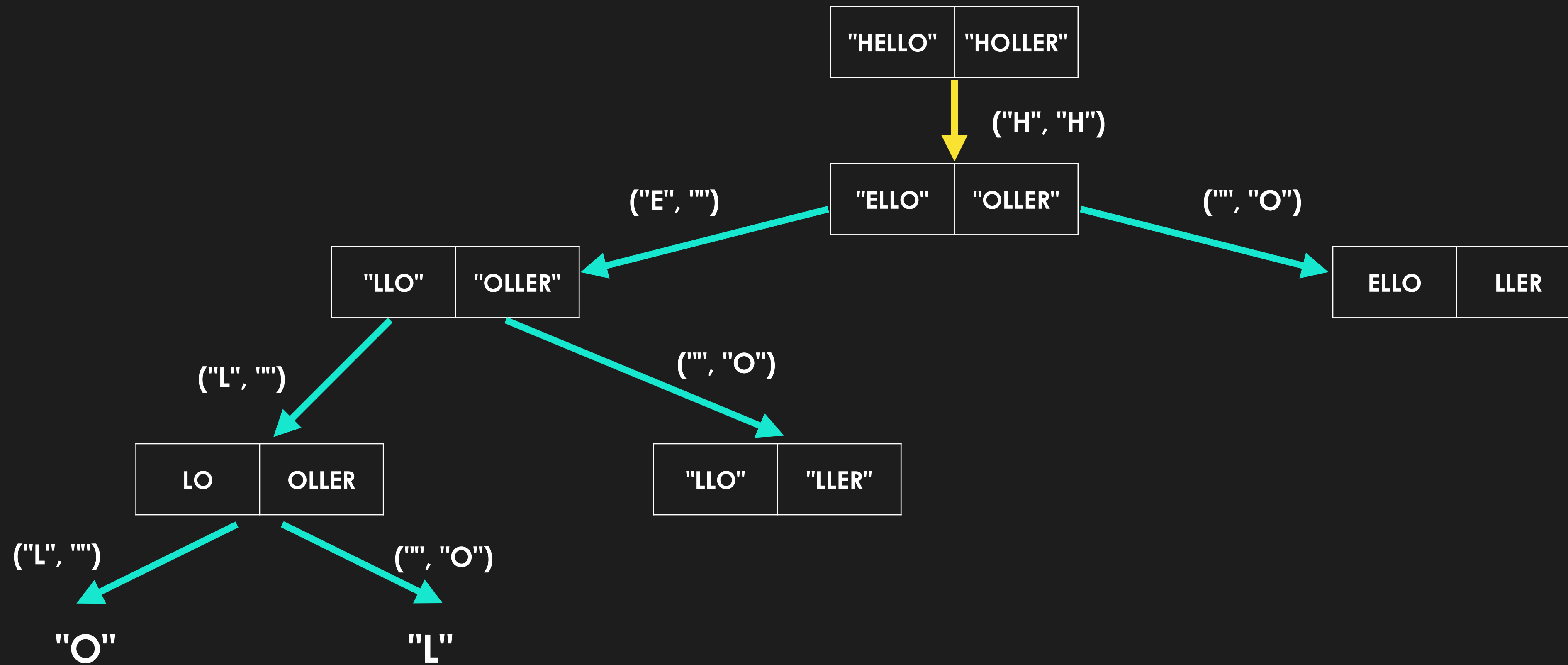
- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure



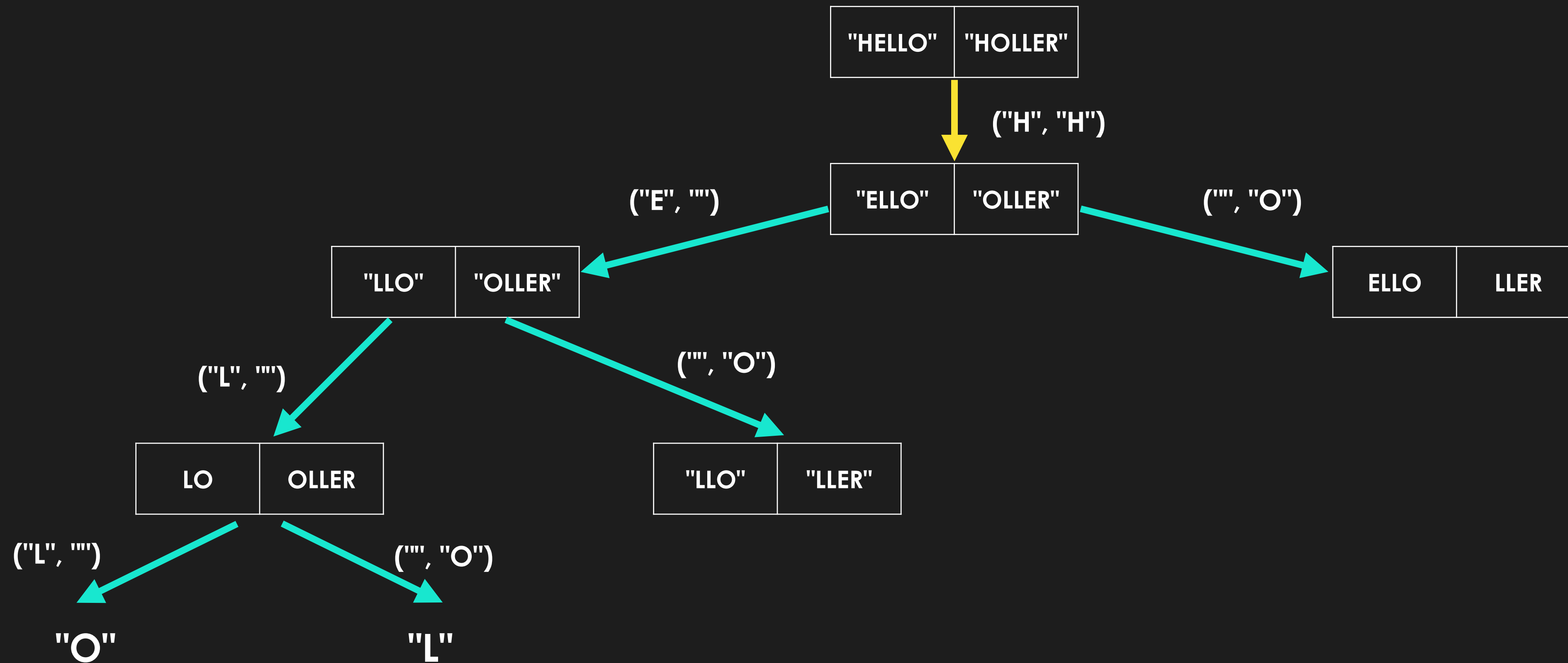
- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure



- **case 1:** first char matches
- **case 2:** first char doesn't match

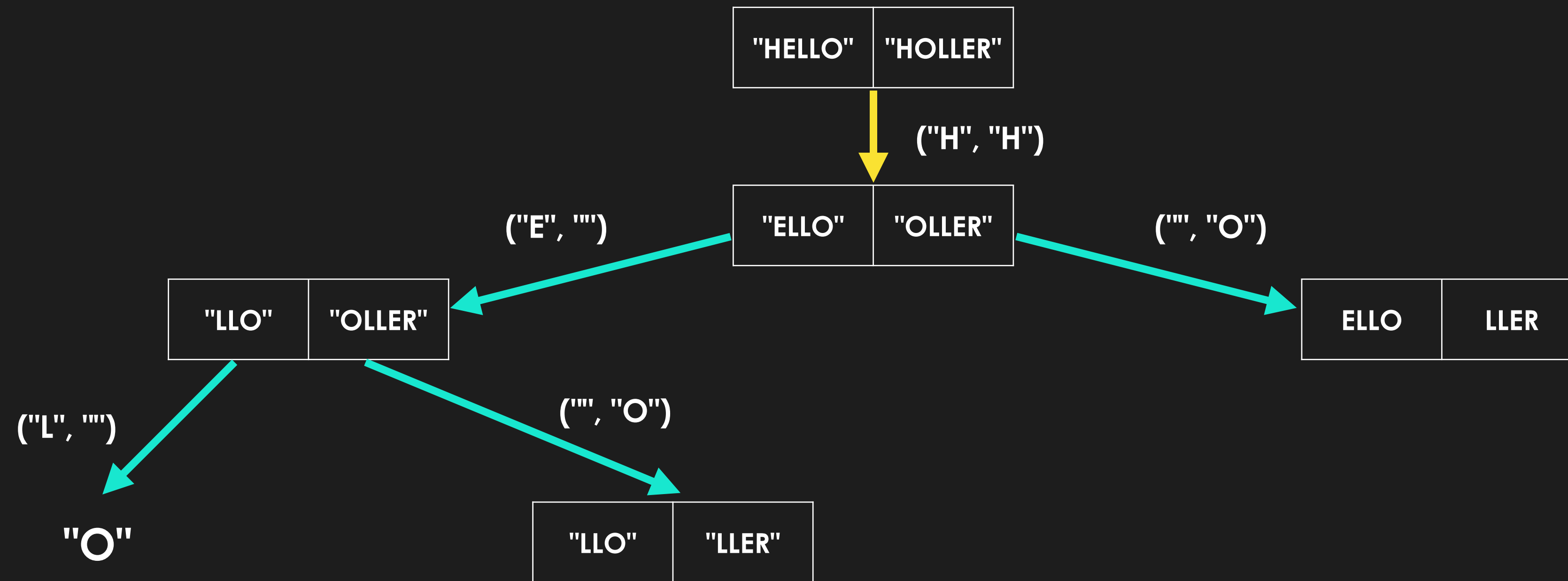
LCS Optimal Substructure



Since "O" and "L" are the same length, return either

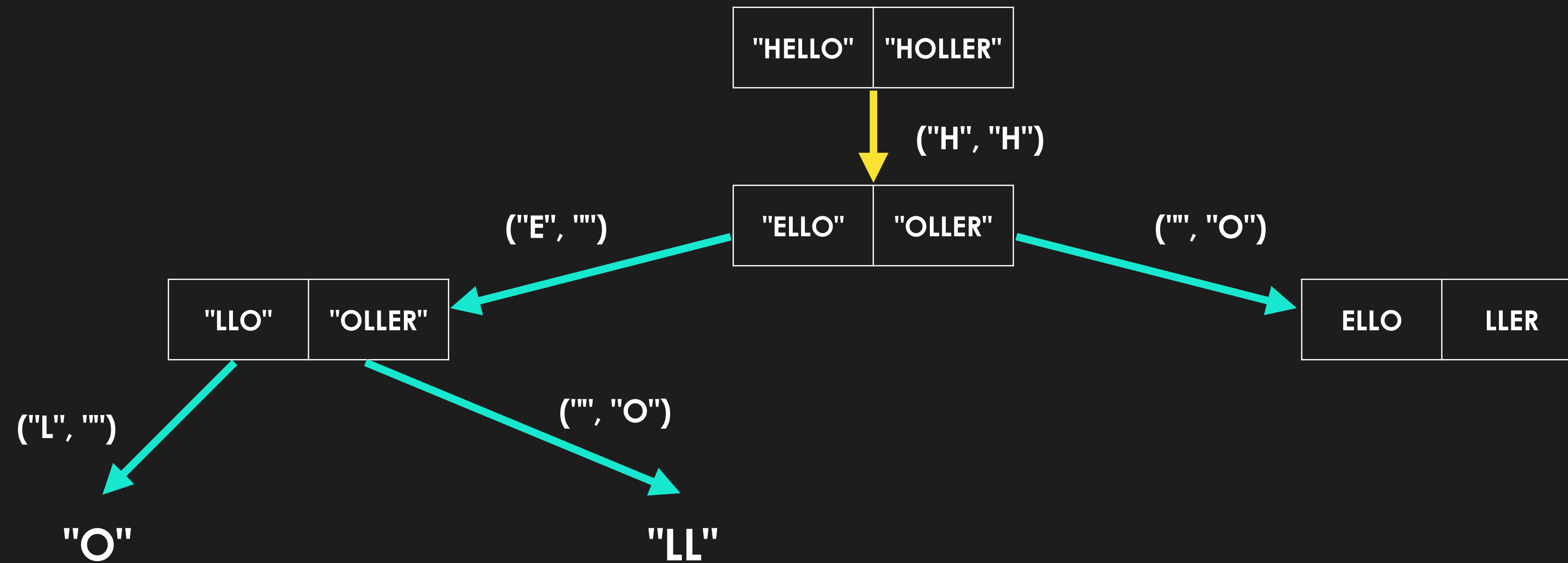
- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure



- **case 1:** first char matches
- **case 2:** first char doesn't match

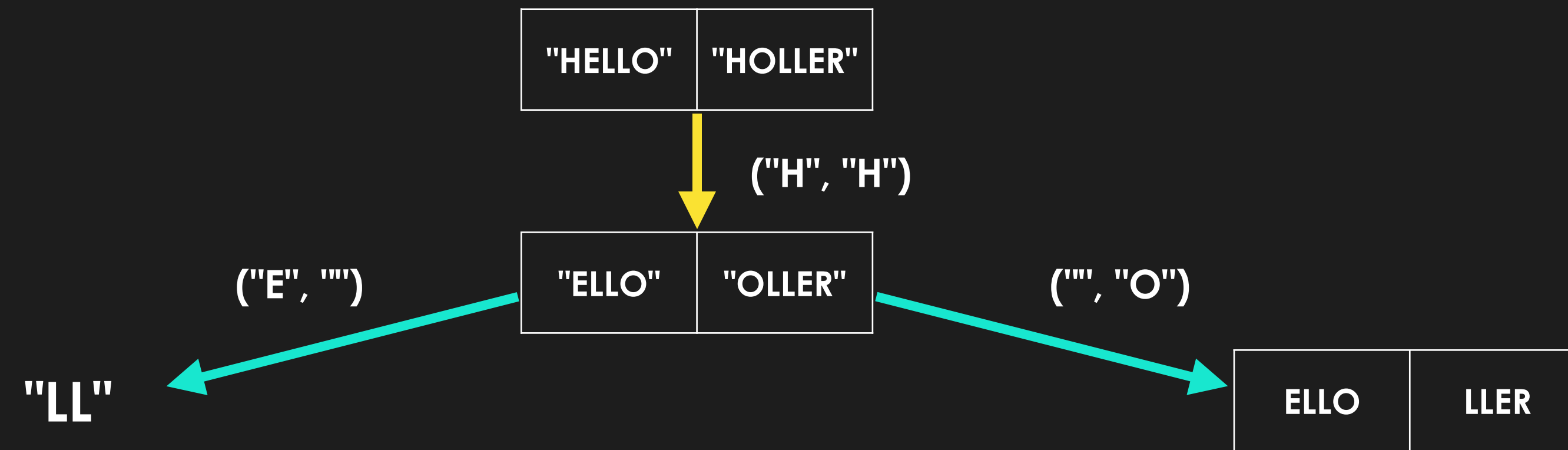
LCS Optimal Substructure



Fast Forward....

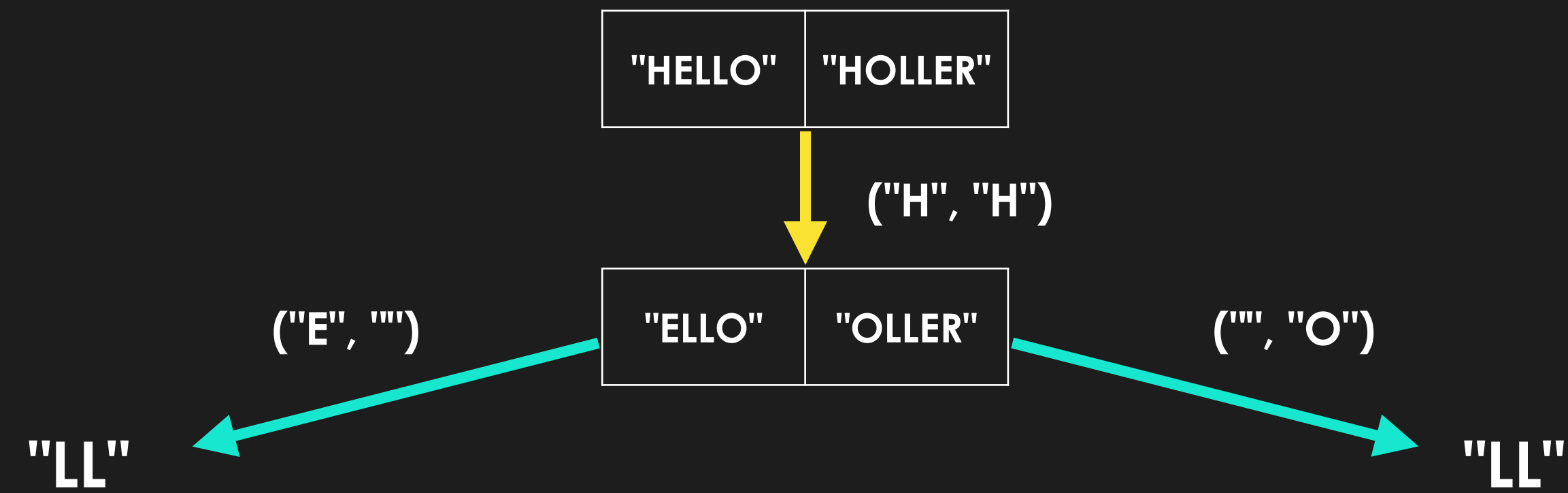
- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure

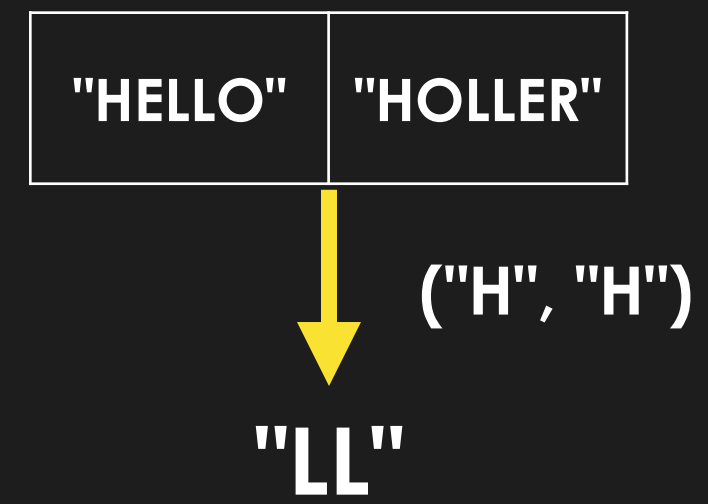


- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure



- **case 1:** first char matches
- **case 2:** first char doesn't match



LCS Optimal Substructure

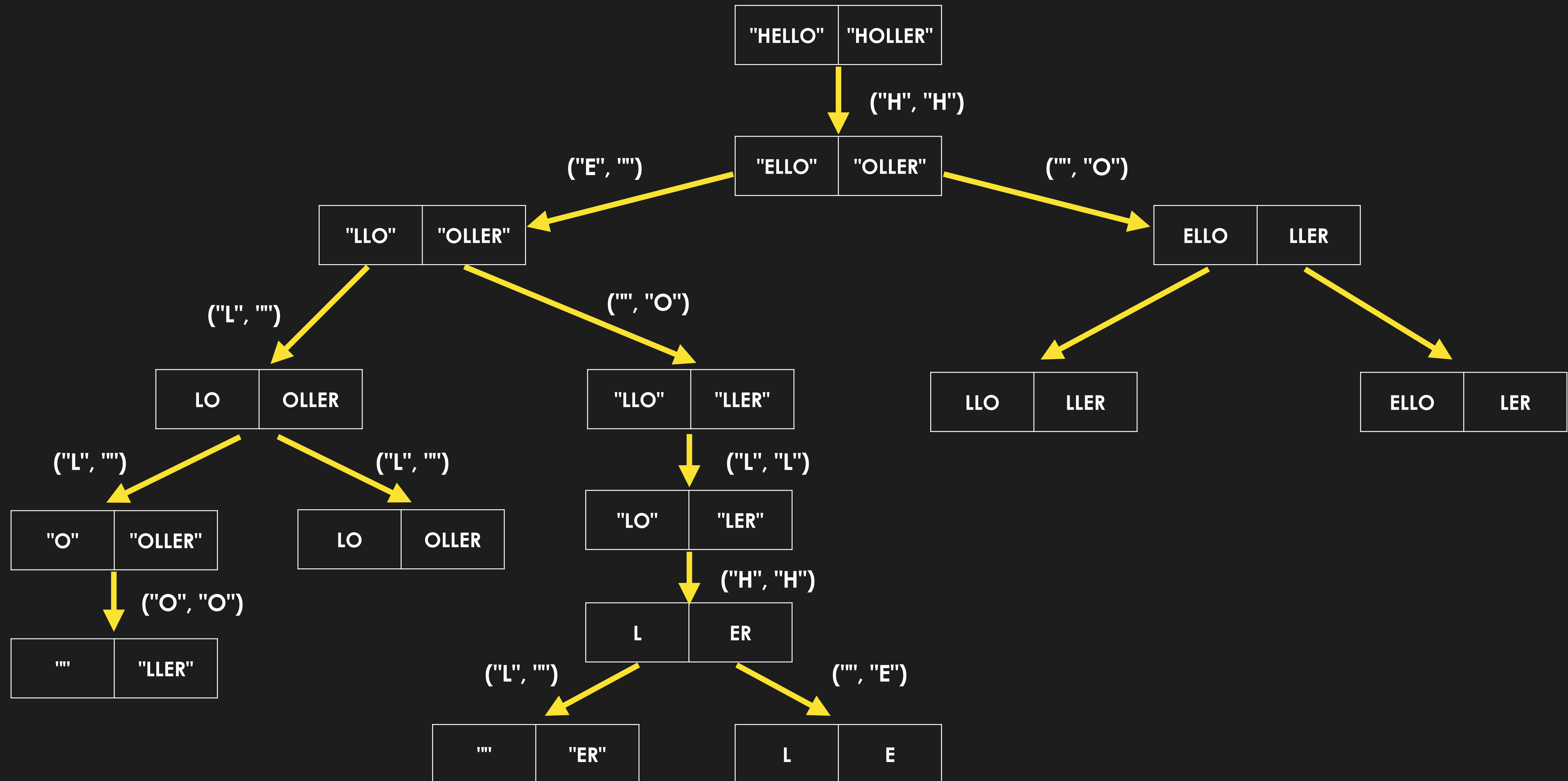
- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure

"HLL"

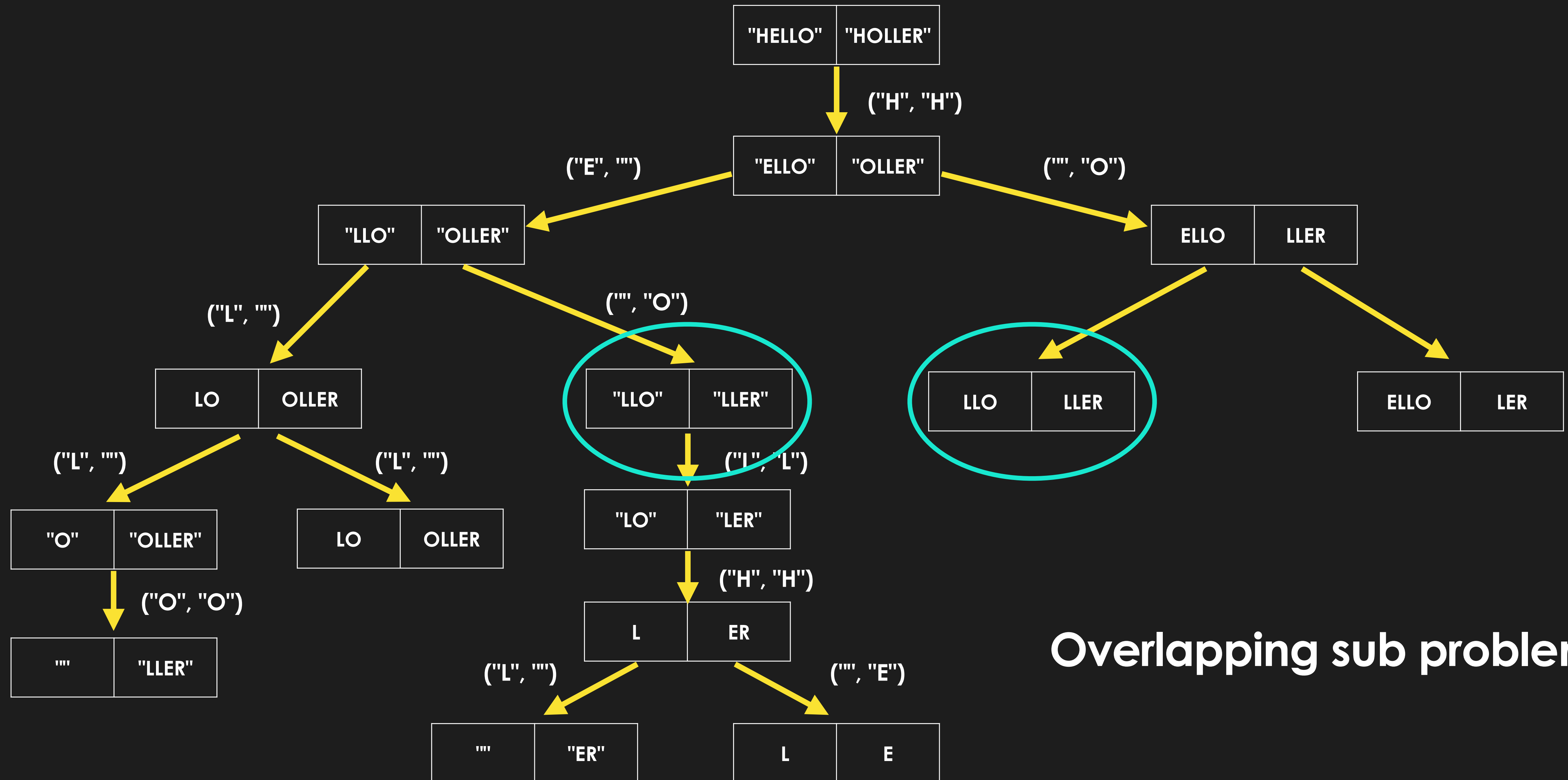
- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure



- **case 1:** first char matches
- **case 2:** first char doesn't match

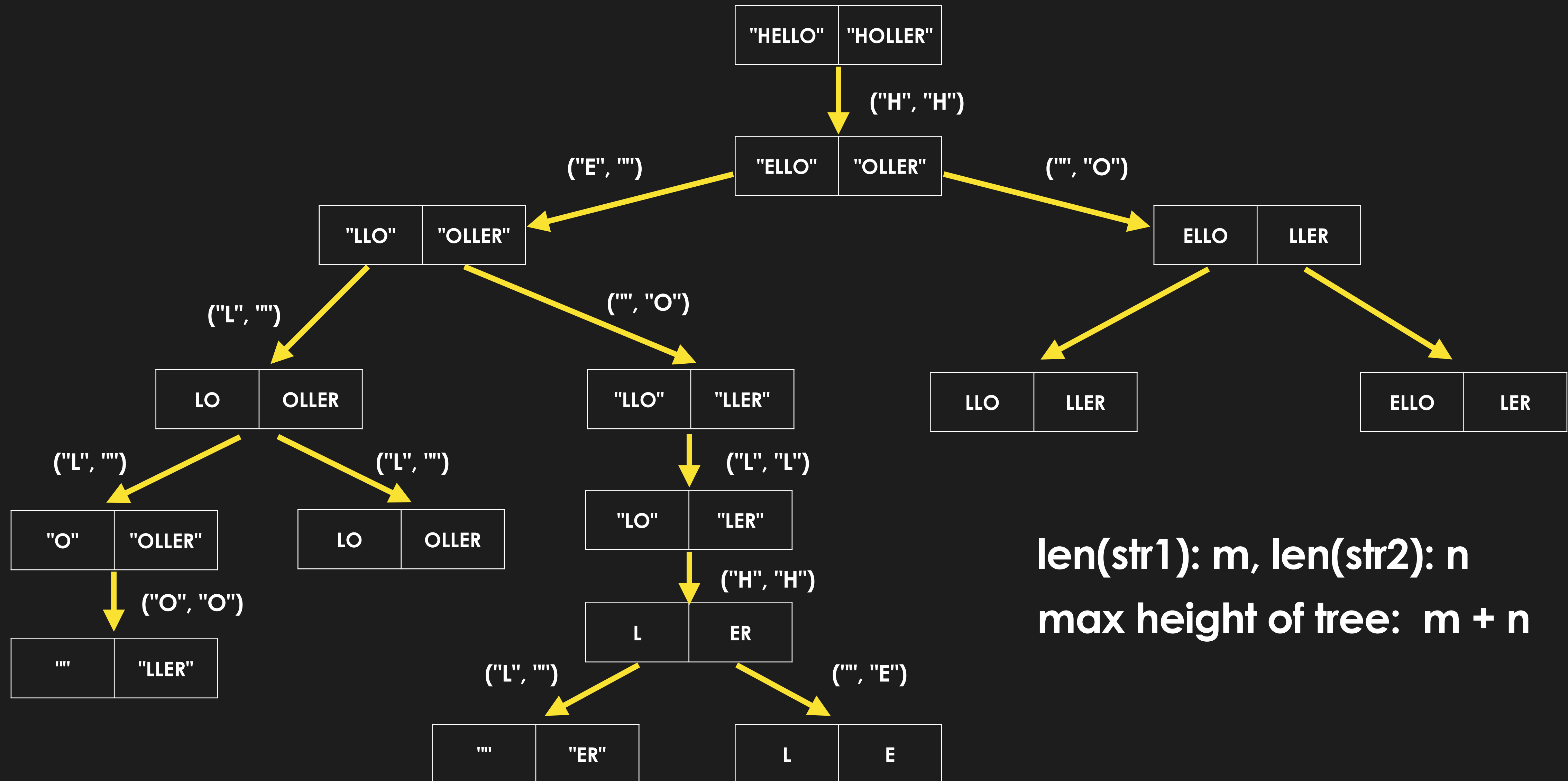
LCS Optimal Substructure



Overlapping sub problems!

- **case 1:** first char matches
- **case 2:** first char doesn't match

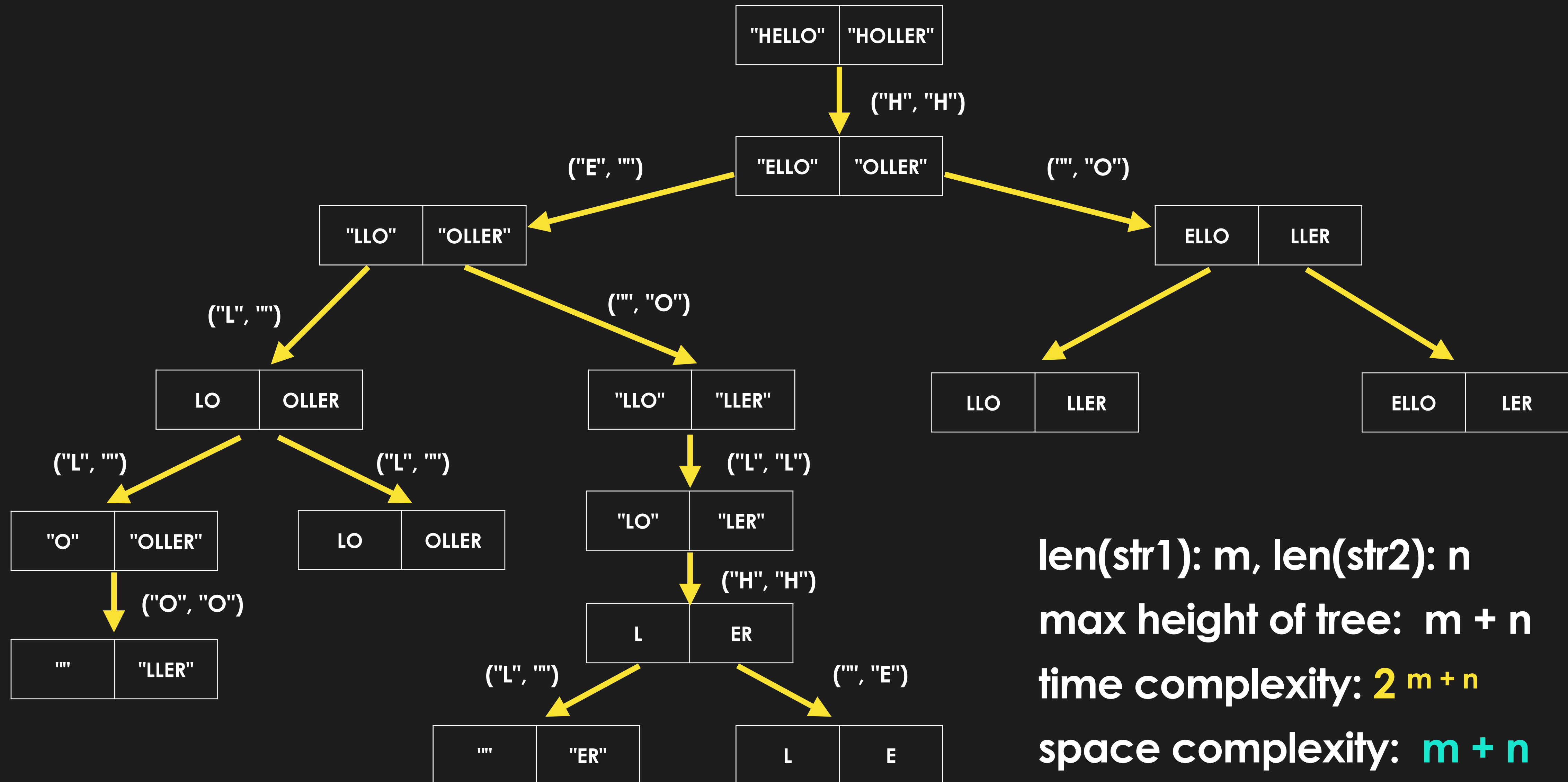
LCS Optimal Substructure



$\text{len}(\text{str1}): m, \text{len}(\text{str2}): n$
 max height of tree: $m + n$

- **case 1:** first char matches
- **case 2:** first char doesn't match

LCS Optimal Substructure



$\text{len}(\text{str1}): m, \text{len}(\text{str2}): n$

max height of tree: $m + n$

time complexity: 2^{m+n}

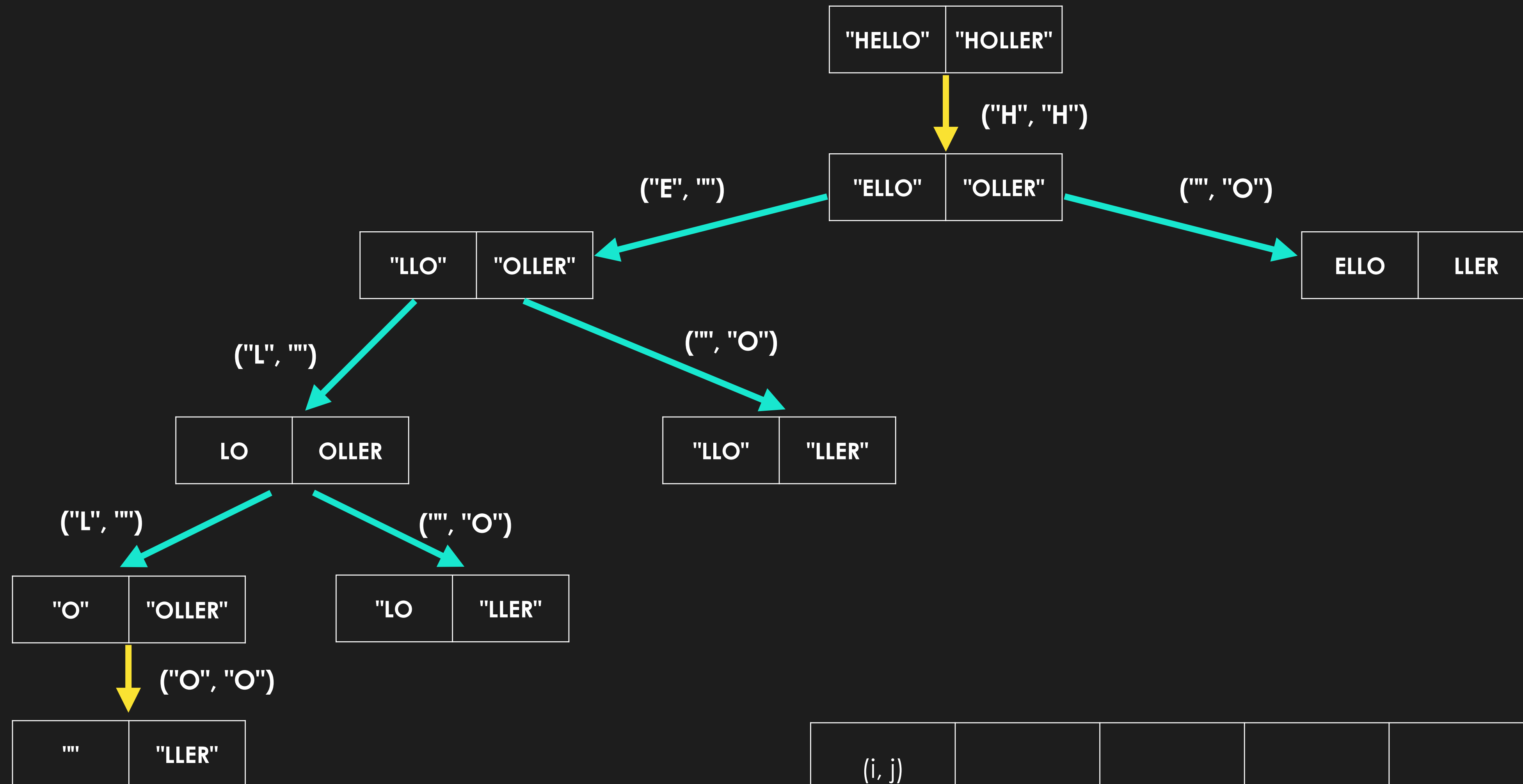
space complexity: $m + n$

LCS

```
def lcsRecurse(string1, string2, i, j):  
    if i >= len(string1) or j >= len(string2):  
        return ""  
  
    if string1[i] == string2[j]:  
        res = lcsRecurse(string1, string2, i + 1, j + 1)  
        return string1[i] + res  
  
    else:  
        res1 = lcsRecurse(string1, string2, i + 1, j)  
        res2 = lcsRecurse(string1, string2, i, j + 1)  
        if len(res1) > len(res2):  
            return res1  
        else:  
            return res2  
  
def longestCommonSubsequence(string1, string2):  
    print(lcsRecurse(string1, string2, 0, 0))
```

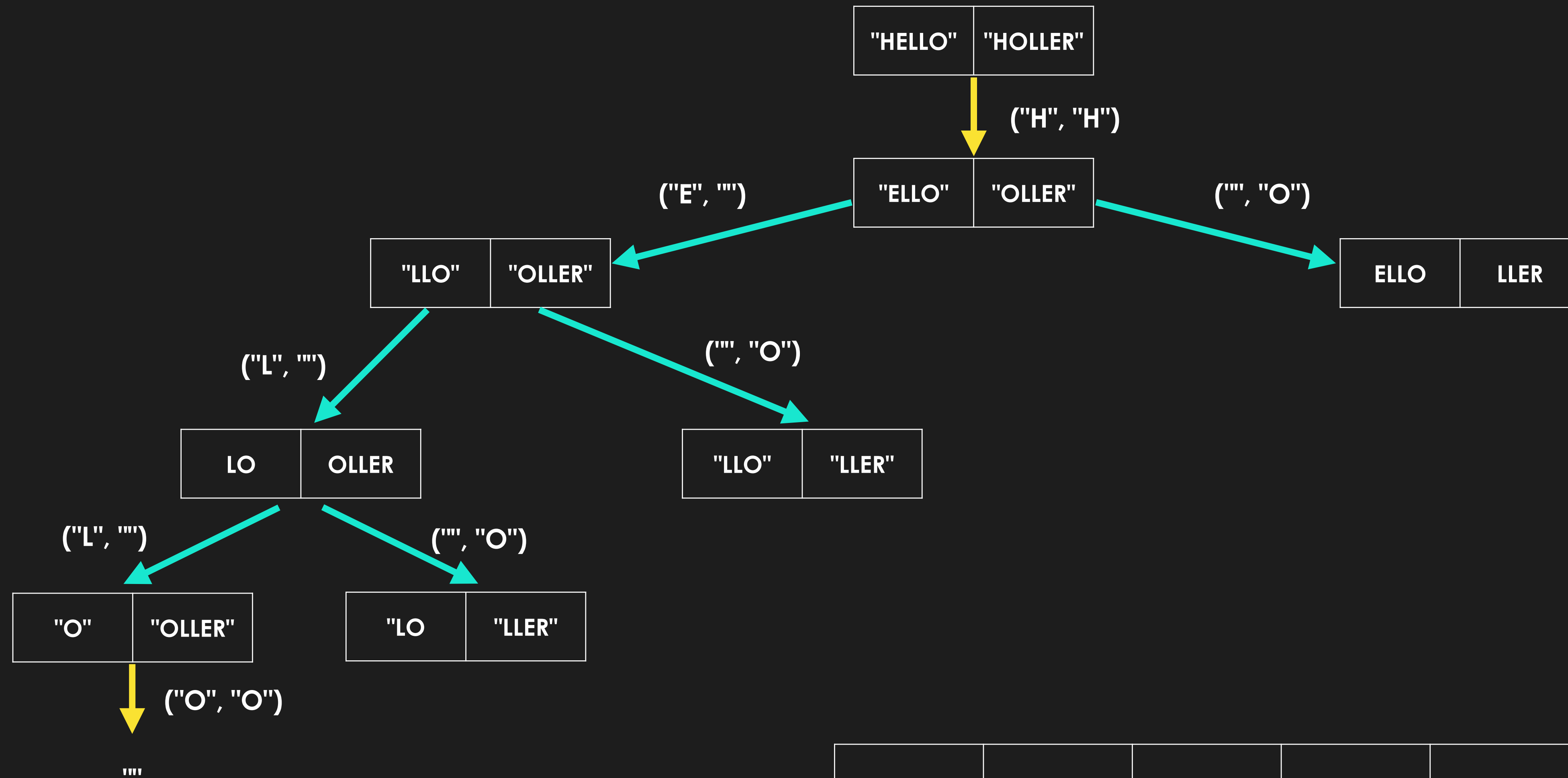
Memoization!

LCS Memo



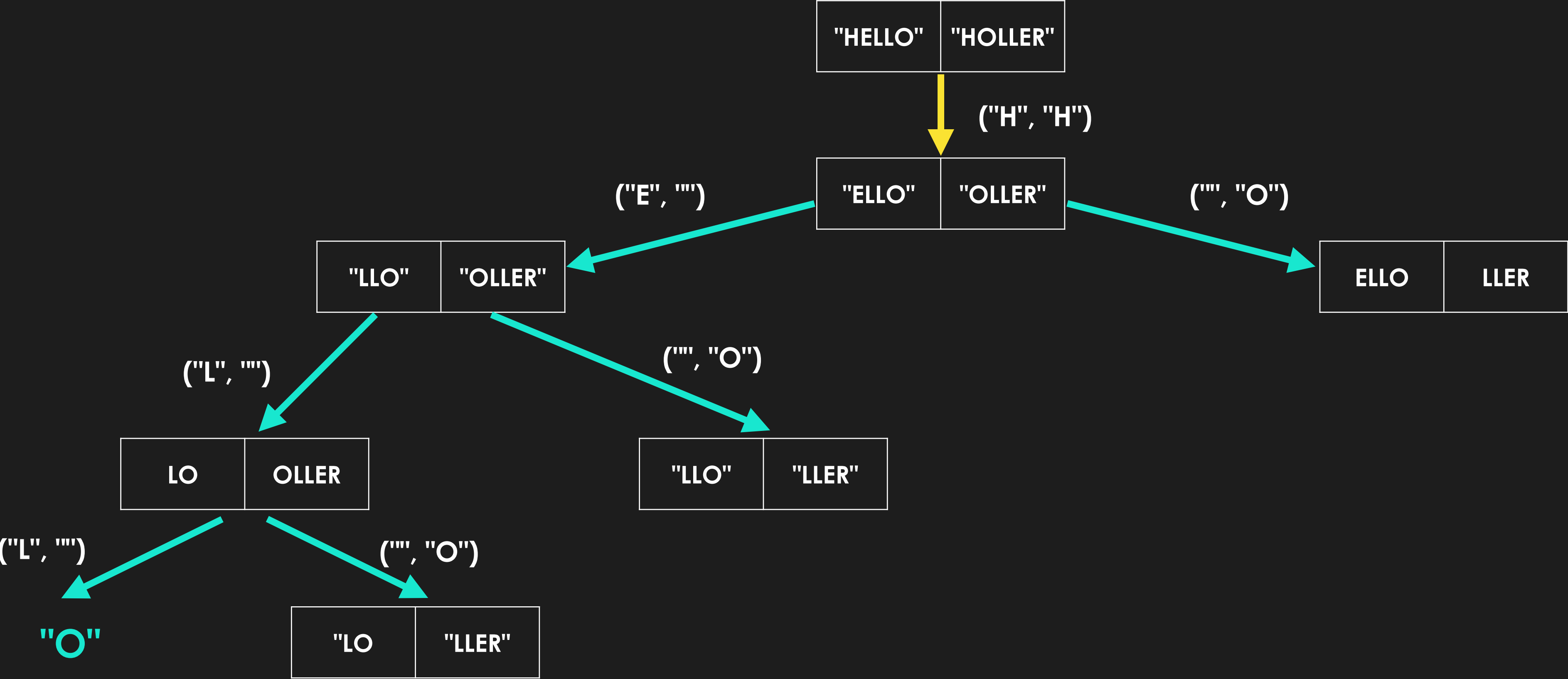
(i, j)						
mem						

LCS Memo



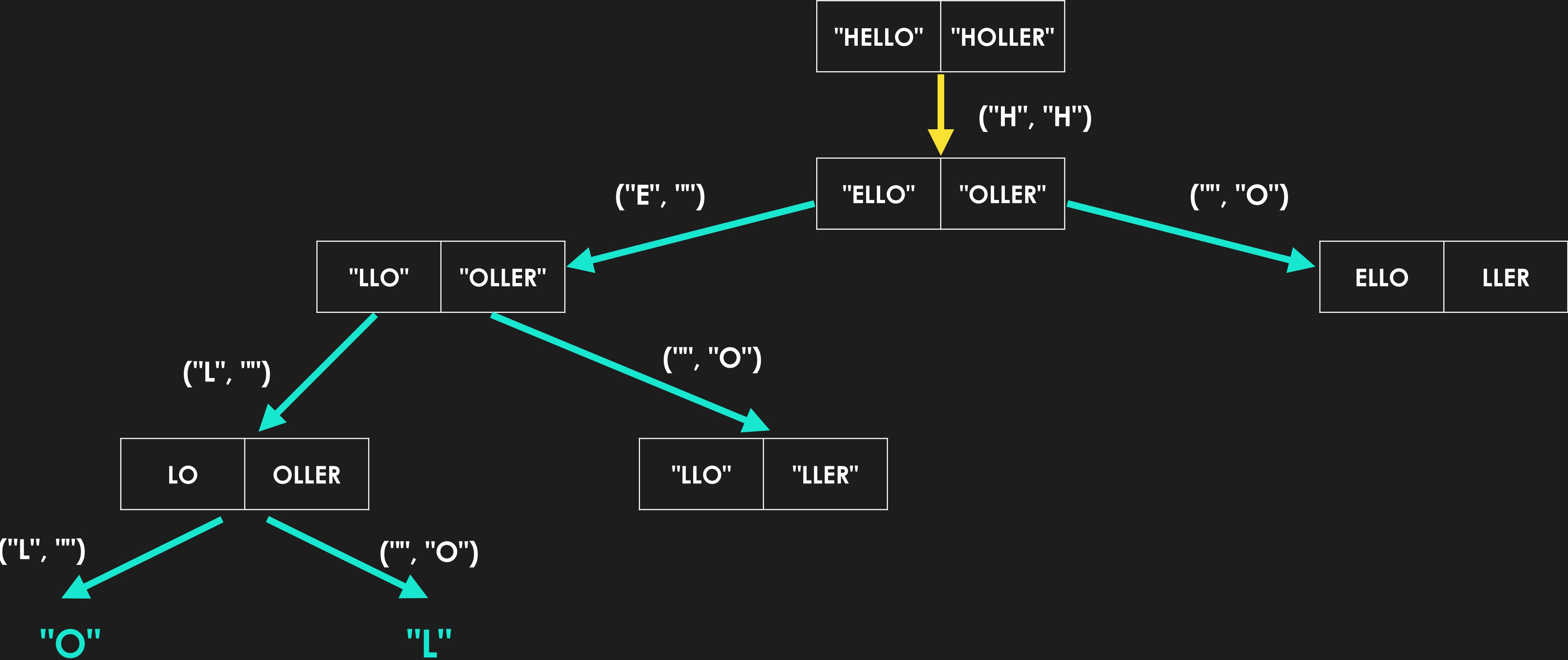
(i, j)						
mem						

LCS Memo



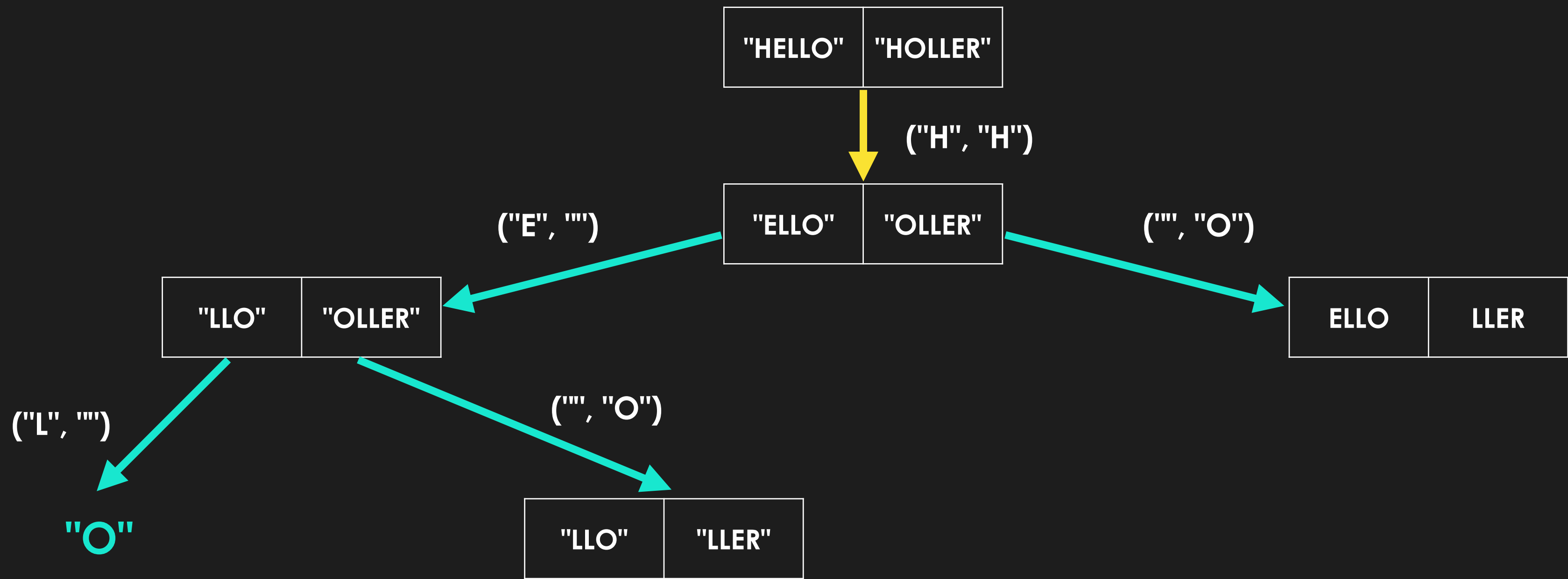
(i, j)	("O", "OLLER")					
mem	"O"					

LCS Memo



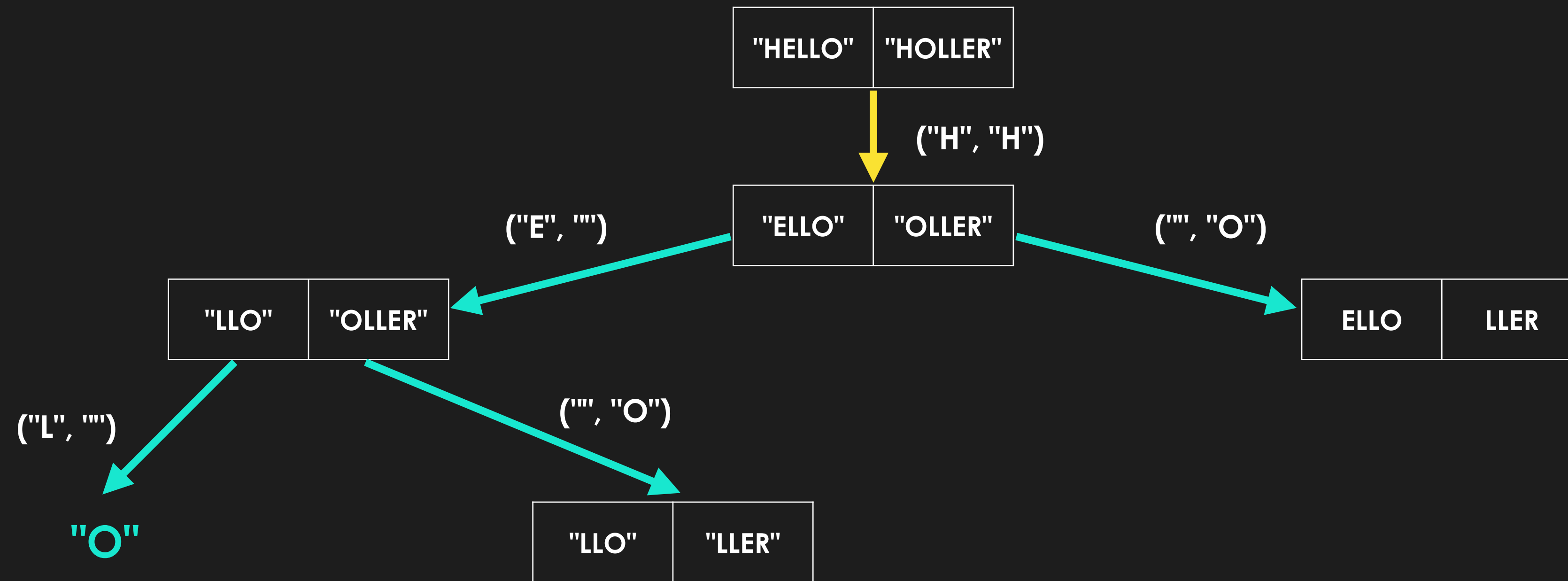
(i, j)	("O", "OLLER")	("LO", "LLER")				
mem	"O"	"L"				

LCS Memo



(i, j)	("O", "OLLER")	("LO", "LLER")	("LO", "OLLER")			
mem	"O"	"L"	"O"			

LCS Memo



time complexity: $m * n$

space complexity: $m + n$

(i, j)	("O", "OLLER")	("LO", "LLER")	("LO", "OLLER")			
mem	"O"	"L"	"O"			

LCSMemo

```
def longestCommonSubsequenceMemo(string1, string2):  
    memo = {}  
    return lcsMemoRecurse(string1, string2, 0, 0, memo)
```

LCSMemo

```
def lcsMemoRecurse(string1, string2, i, j, memo):  
    if (i, j) in memo:  
        return memo[(i, j)]  
  
    if i >= len(string1) or j >= len(string2):  
        return ""  
  
    if string1[i] == string2[j]:  
        sub = lcsMemoRecurse(string1, string2, i + 1, j + 1, memo)  
        memo[(i, j)] = string1[i] + sub  
        return string1[i] + sub  
  
    else:  
        sub1 = lcsMemoRecurse(string1, string2, i + 1, j, memo)  
        sub2 = lcsMemoRecurse(string1, string2, i, j + 1, memo)  
        result = sub1 if len(sub1) > len(sub2) else sub2  
        memo[(i, j)] = result  
        return result
```

Takeaways from memoization

1. Memoization reduces time complexity from **exponential to polynomial**
2. The memoized time complexity of a recursive implementation becomes the **height of the tree**

Lab Session 1

Lab Session 1

- In this lab session, you will be implementing **memoization.py**
- Your task is to implement **the following functions:**

1. fib:

- o Takes in an int n and returns the nth number in the fibonacci sequence
- o This function should run in **$O(N)$ time**

2. bestSum:

- o Takes in an array of integers and a target sum
- o Should return an array of any combination of integers included in the array, with repeats allowed, which sum to the target
- o This array should be the of the smallest size possible, or empty if there is no solution
- o Should run in **$O(NM^2)$ time**, where N is the length of the array and M is the target sum

Lab Session 1

3. **longestCommonSubsequence:**

- Takes in two strings string1 & string2
 - Returns the longest common subsequence between string1 & string2 as a string, or an empty string if there is none
 - Should run in **$O(NM)$ time**
-
- All three problems should be done using the memoization method (recursion)
 - All problems take in a memo object as an argument. You may assume the memo is empty for the first recursive call of the function
 - To test the problems, run ``python utils/mem_test.py``

Solution: fib

```
def fib(n: int, memo: Dict):  
    if n in memo:  
        return memo[n]  
  
    if n == 0 or n == 1:  
        return 1  
  
    else:  
        memo[n] = fib(n - 1, memo) + fib(n - 2, memo)  
        return fib(n - 1, memo) + fib(n - 2, memo)
```

Solution: bestSum

```
def bestSum(array: List, targetSum: int, memo: Dict):  
    if targetSum in memo:  
        return memo[targetSum]  
  
    if targetSum == 0:  
        return []  
  
    if targetSum < 0:  
        return None  
  
    bestArr = None  
  
    for num in array:  
        newTarget = targetSum - num  
        res = bestSum(array, newTarget, memo)  
        if res is not None:  
            if bestArr is None or len(res) + 1 < len(bestArr):  
                bestArr = res.copy()  
                bestArr.append(num)  
  
    memo[targetSum] = bestArr  
    return bestArr
```

Solution: longestCommonSubsequence

```
def lcsMemoRecurse(string1, string2, i, j, memo):
    if (i, j) in memo:
        return memo[(i, j)]

    if i >= len(string1) or j >= len(string2):
        return ""

    if string1[i] == string2[j]:
        sub = lcsMemoRecurse(string1, string2, i + 1, j + 1, memo)
        memo[(i, j)] = string1[i] + sub
        return string1[i] + sub

    else:
        sub1 = lcsMemoRecurse(string1, string2, i + 1, j, memo)
        sub2 = lcsMemoRecurse(string1, string2, i, j + 1, memo)
        result = sub1 if len(sub1) > len(sub2) else sub2
        memo[(i, j)] = result
        return result

def longestCommonSubsequence(string1: str, string2: str, memo: Dict):
    return lcsMemoRecurse(string1, string2, 0, 0, memo)
```

Tabulation: Bottom Up approach