

Greedy Algorithms

Brute-Force,
Heuristic Algorithms



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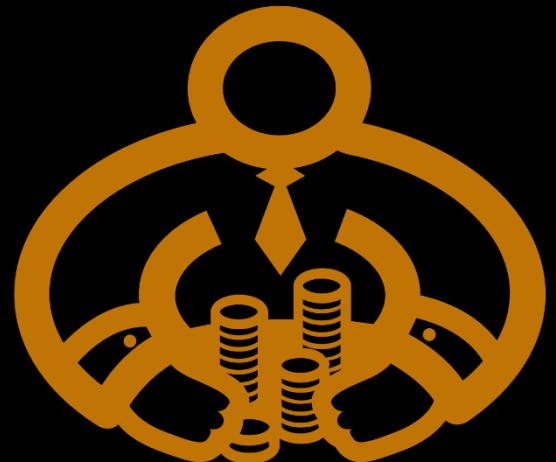
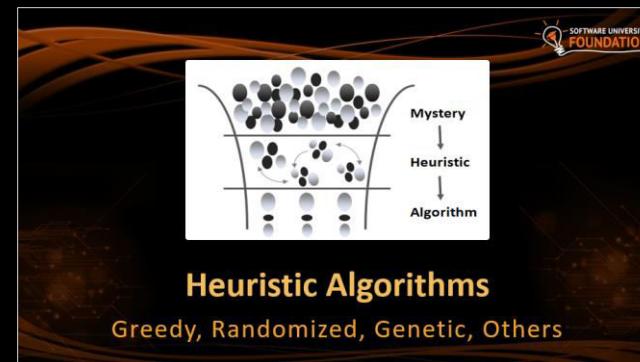
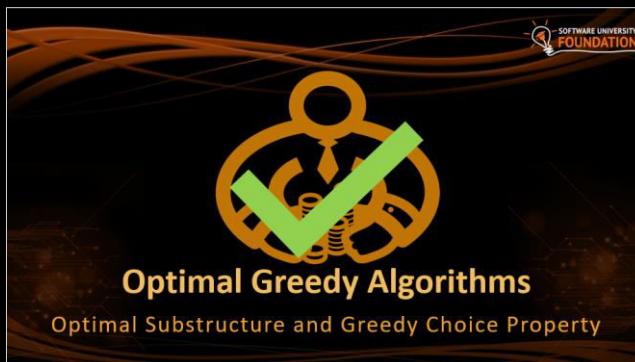


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Have a Question?



sli.do

#DsAlgo



Brute-Force Algorithms

Trying All Solutions

Brute-Force Algorithms

- Trying all possible combinations
- Picking the best solution
- Usually slow and inefficient



0 0 0 0 0

Brute-Force Algorithms

0 0 0 0 0

Brute-Force Algorithms

00001

Brute-Force Algorithms

00002

Brute-Force Algorithms

00003

Brute-Force Algorithms

00010

Brute-Force Algorithms

9 9 9 9 8

Brute-Force Algorithms

9 9 9 9 9

Brute-Force Algorithms

9 9 9 9 9

$10 \times 10 \times 10 \times 10 \times 10 = 100,000$ combinations



Greedy Algorithms

Picking Locally Optimal Solution

Optimization Problems

- In computer science, an **optimization problem** is the problem of finding the best solution from all feasible solutions
 - Finding the **optimal** among **many** candidates
- Examples of optimization problems:
 - Find the **shortest path** from Sofia to Varna on the map
 - Find the **maximum increasing subsequence** in integer sequence
 - **Traveling salesman problem** (minimal Hamilton cycle)
 - Find the shortest route that visits each city and returns to the origin city

Greedy Algorithms

- Greedy algorithms are a category of algorithms
 - For solving optimization problems
 - Usually more efficient than the other algorithms
 - But can produce non-optimal (incorrect) result
- Greedy algorithms pick the best local solution
 - Pick the optimum from their current position & point of view
- Greedy algorithms assume always choosing a local optimum leads to the global optimum
 - This is sometimes correct, but sometimes it is not



Sum of Coins Problem

Greedy Algorithms: Sum of Coins

- Consider the US currency coins:
 - { 0.01, 0.02, 0.05, 0.10 }
- Problem "Sum of Coins":
 - Gather a sum of money, using the least possible number of coins
- Greedy algorithm for "Sum of Coins":
 - Take the largest coin while possible
 - Then take the second largest
 - Etc.

Sum of Coins Visualization

Target: 18



Actual: 0

Sum of Coins Visualization

Target: 18



Actual: 10



Sum of Coins Visualization

Target: 18



Actual: 15



Sum of Coins Visualization

Target: 18



Actual: 17



Sum of Coins Visualization

Target: 18



Actual: 18



Sum of Coins – Solution

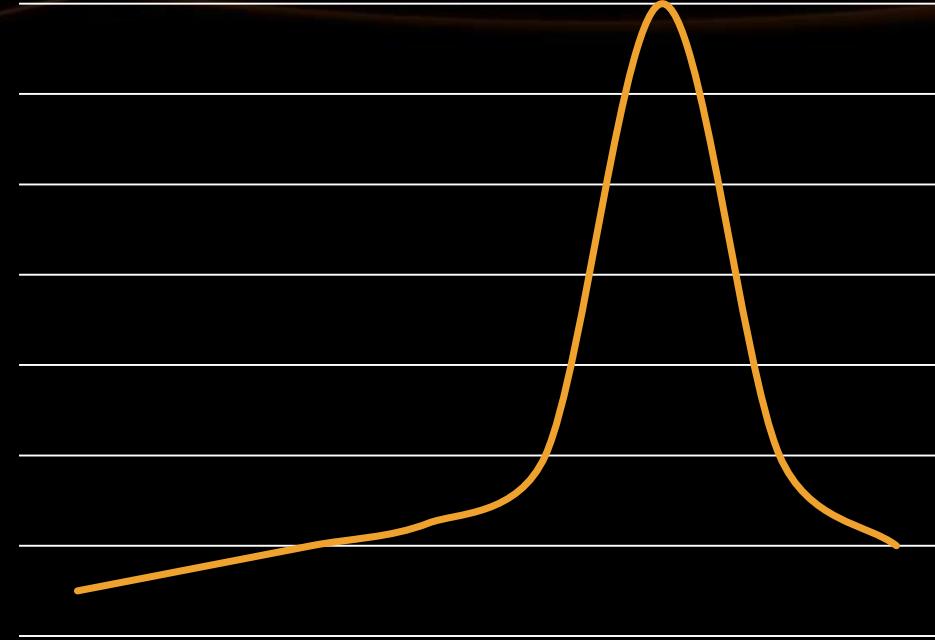
```
int finalSum = 18;  
int currentSum = 0;  
int[] coins = { 10, 10, 5, 5, 2, 2, 1, 1 };  
Queue<int> resultCoins = new Queue<int>();  
  
// Next Slide  
  
Console.WriteLine("Sum not found");
```

Sum of Coins – Solution(2)

```
for (int i = 0; i < coins.Length; i++)
{
    if (currentSum + coins[i] > finalSum) continue;

    currentSum += coins[i];
    resultCoins.Enqueue(coins[i]);

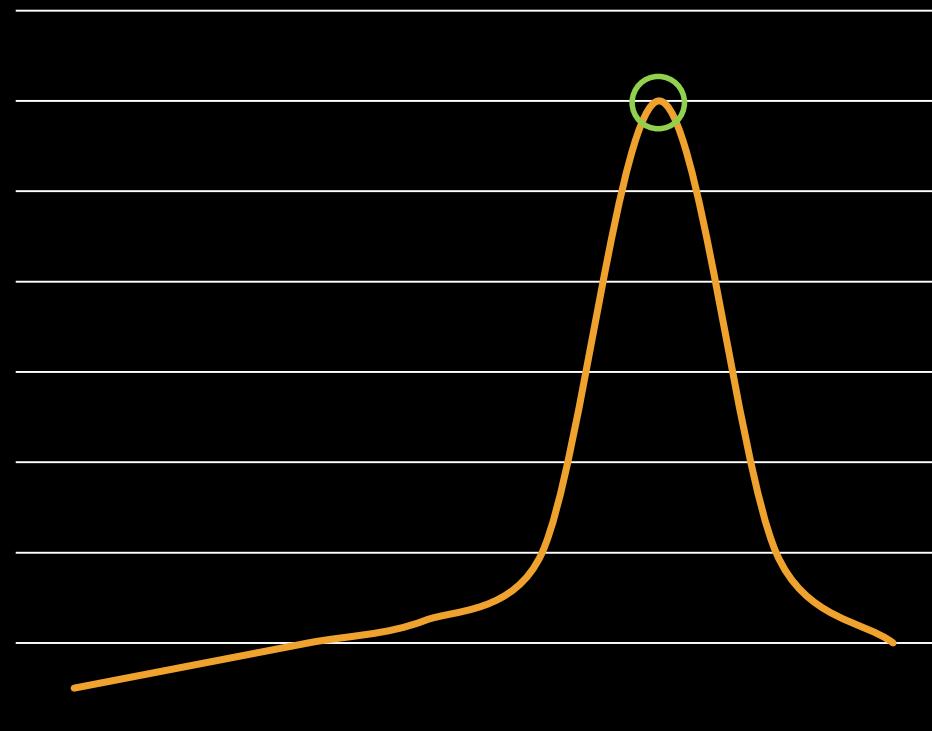
    if (currentSum == finalSum)
        // Sum Found
}
```



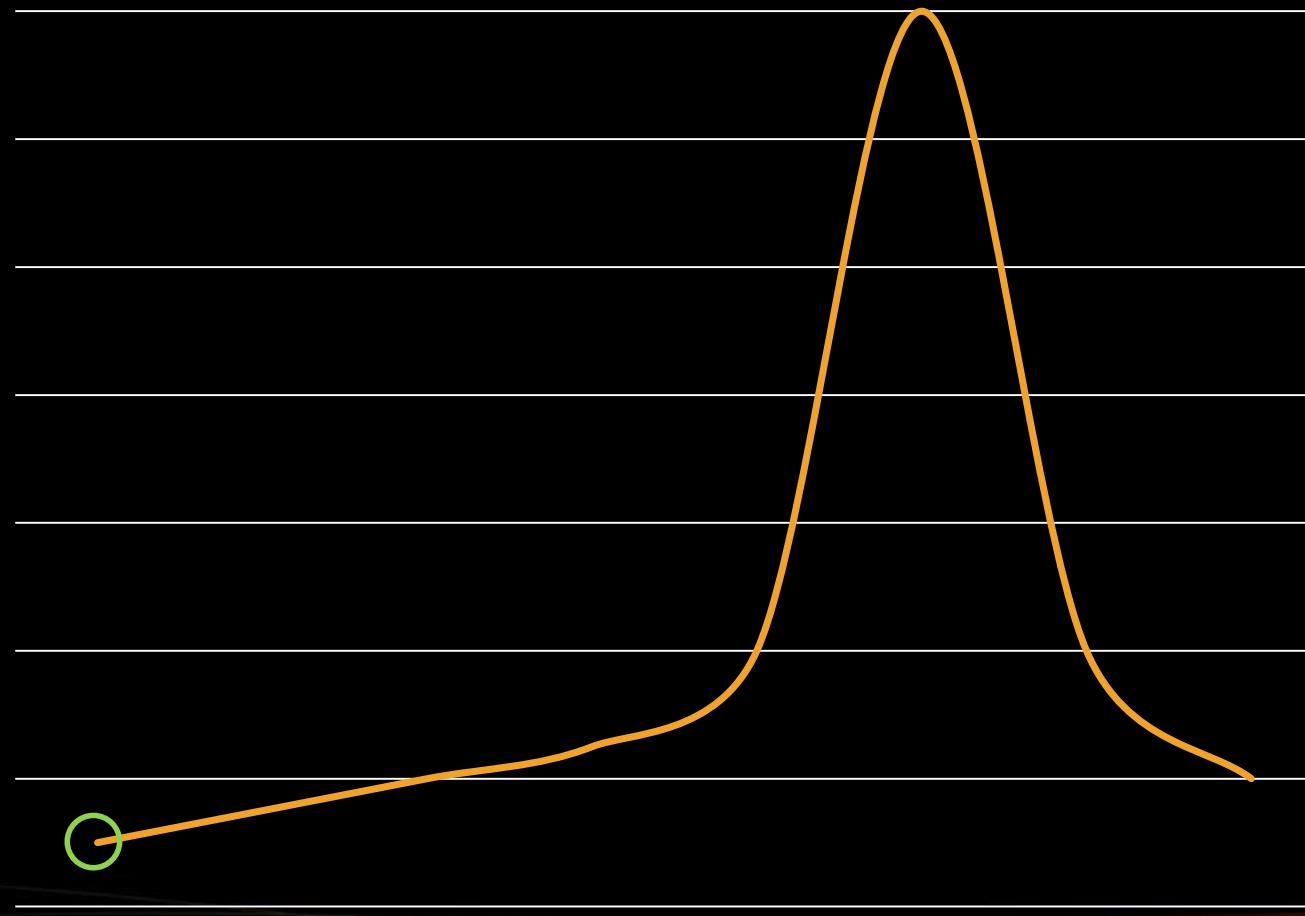
Peak Point Problem

Greedy Algorithms: Peak Point

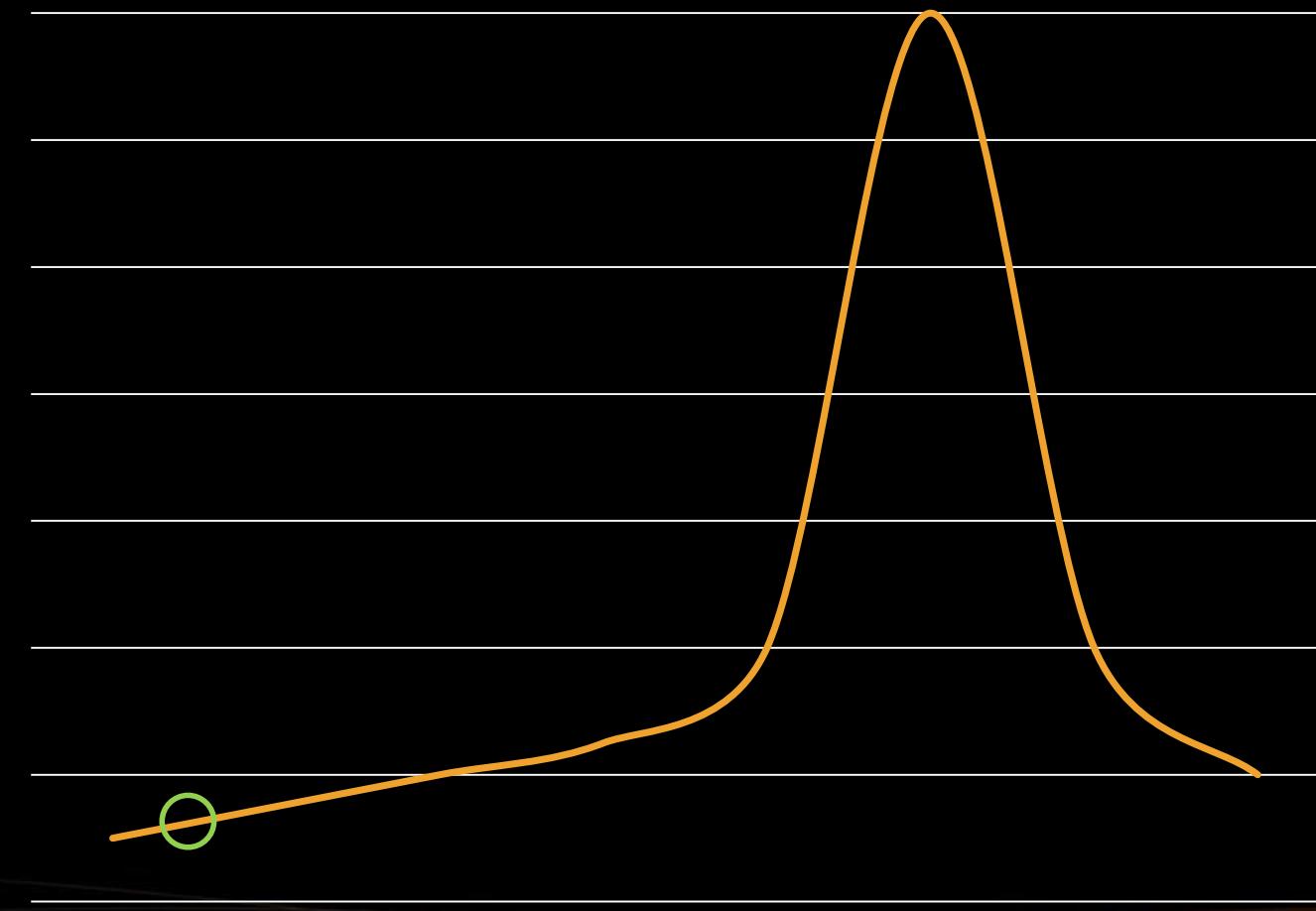
- Find the peak point on a curve



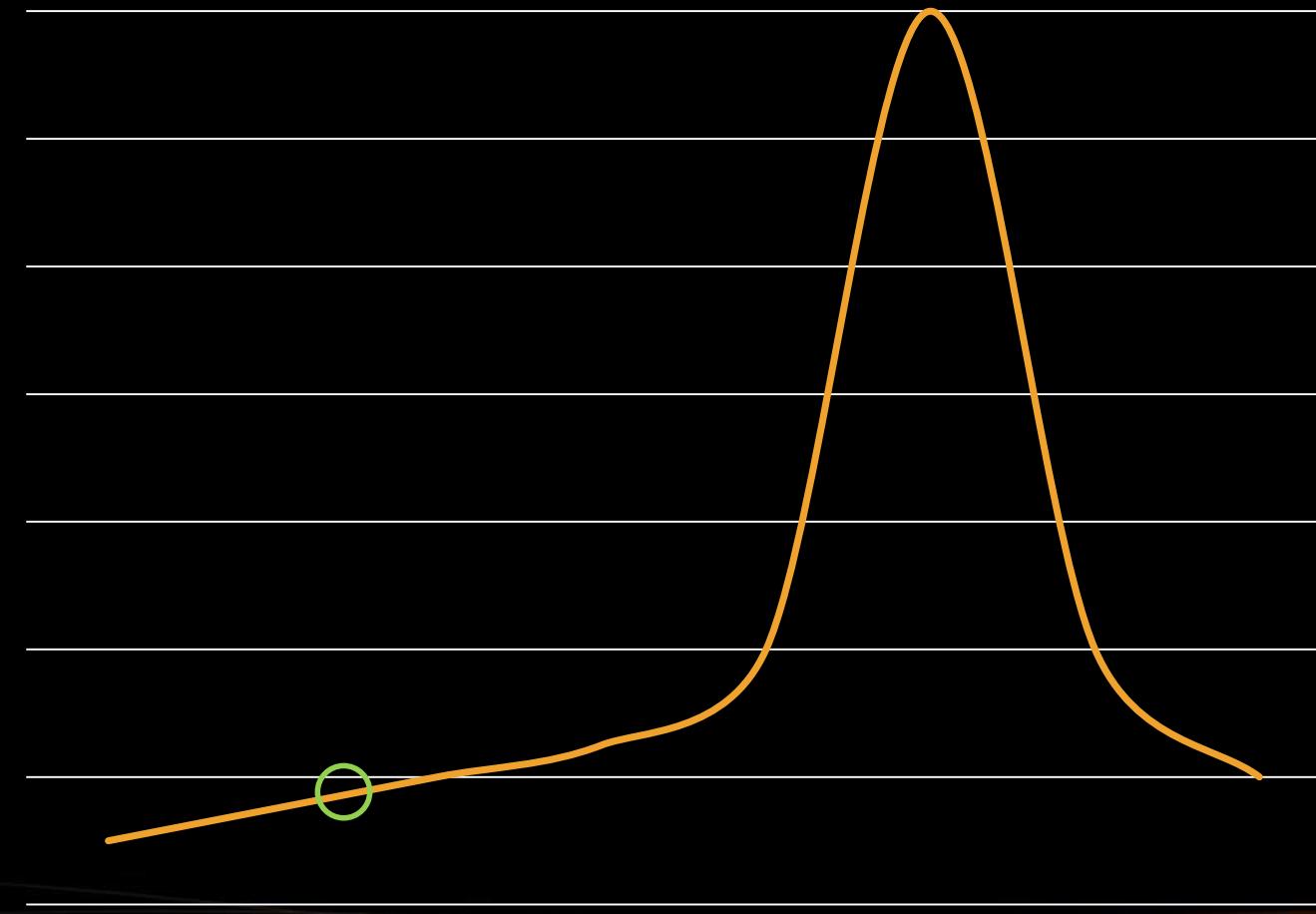
Peak Point Visualization



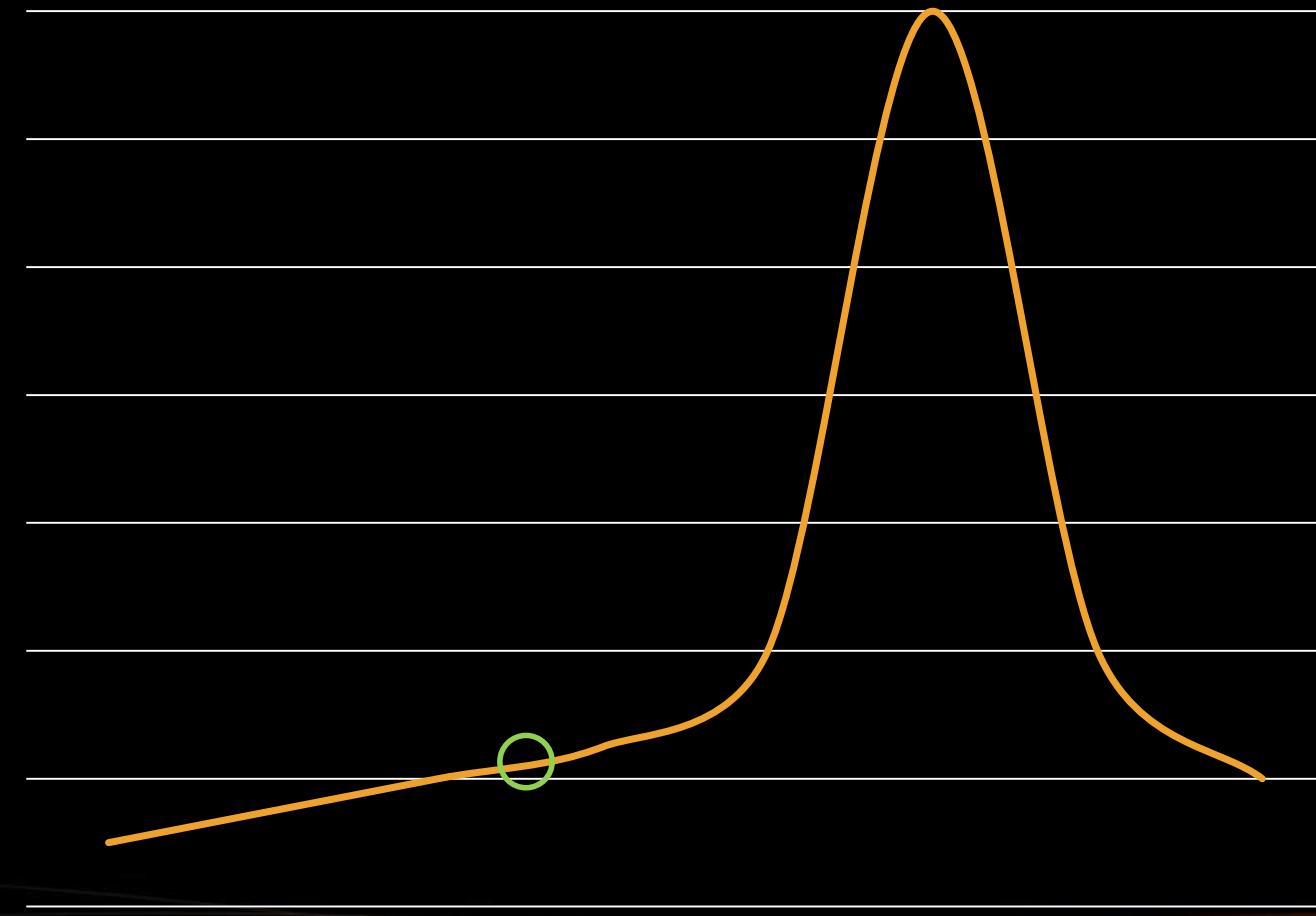
Peak Point Visualization



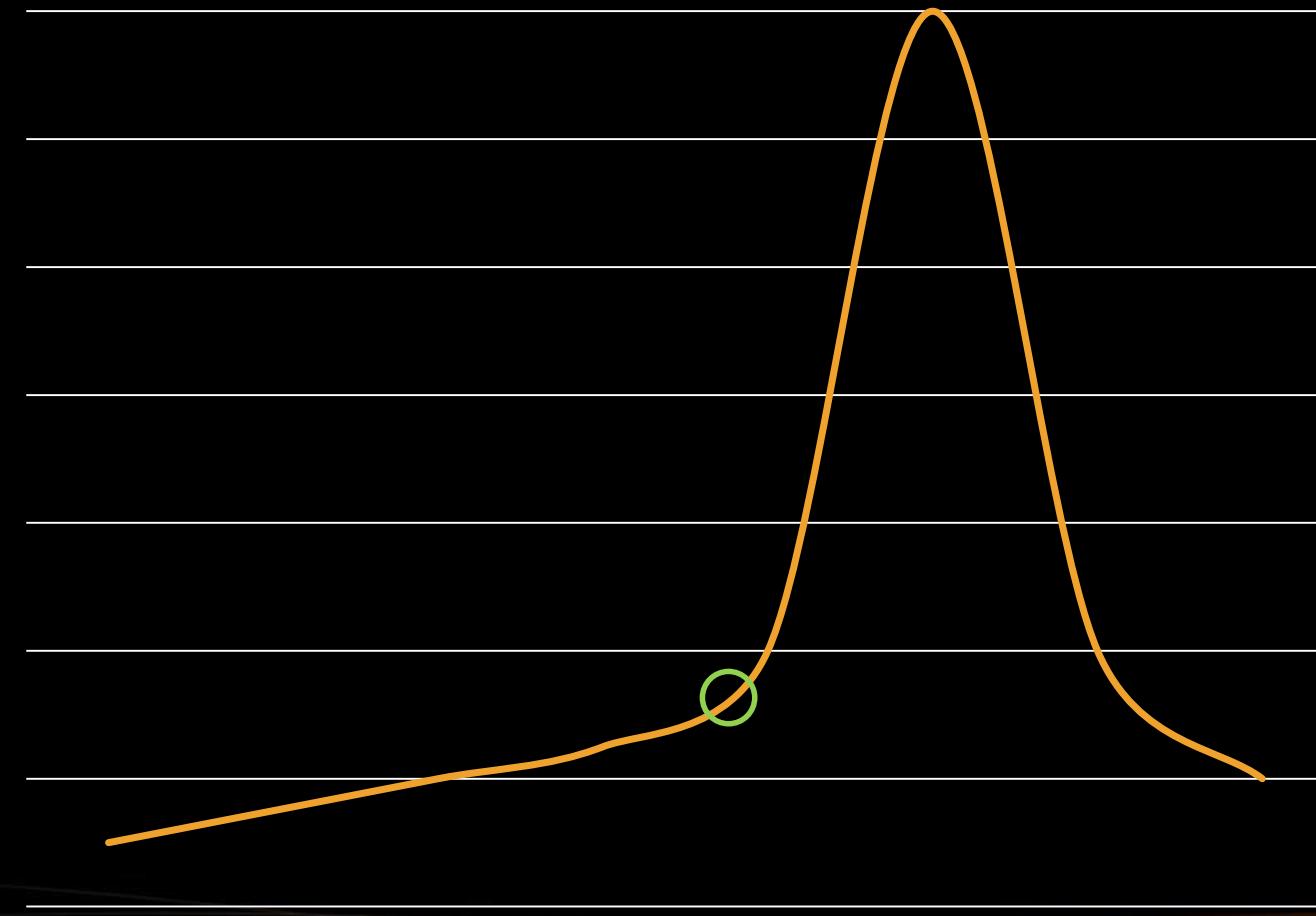
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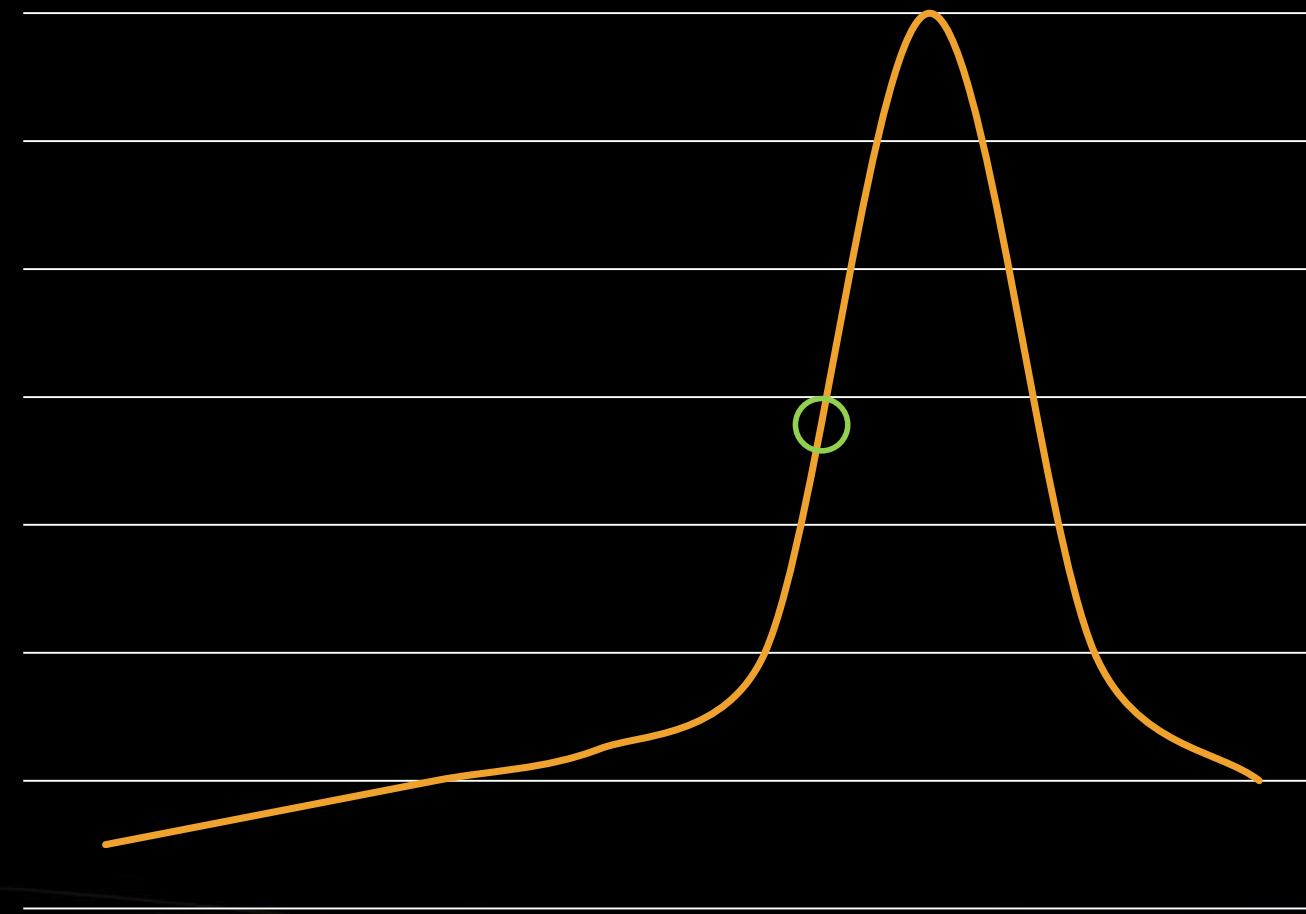
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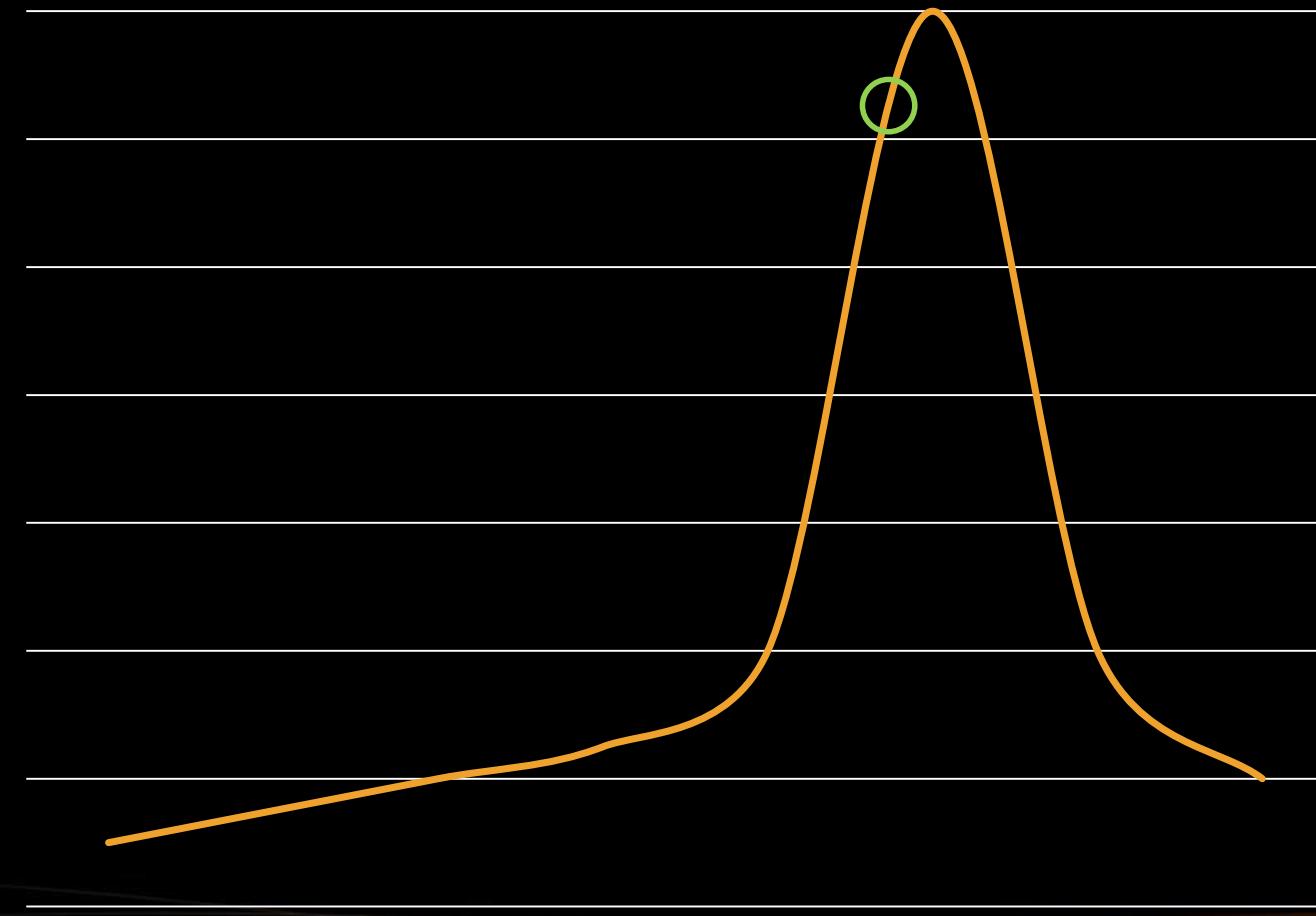
Peak Point Visualization



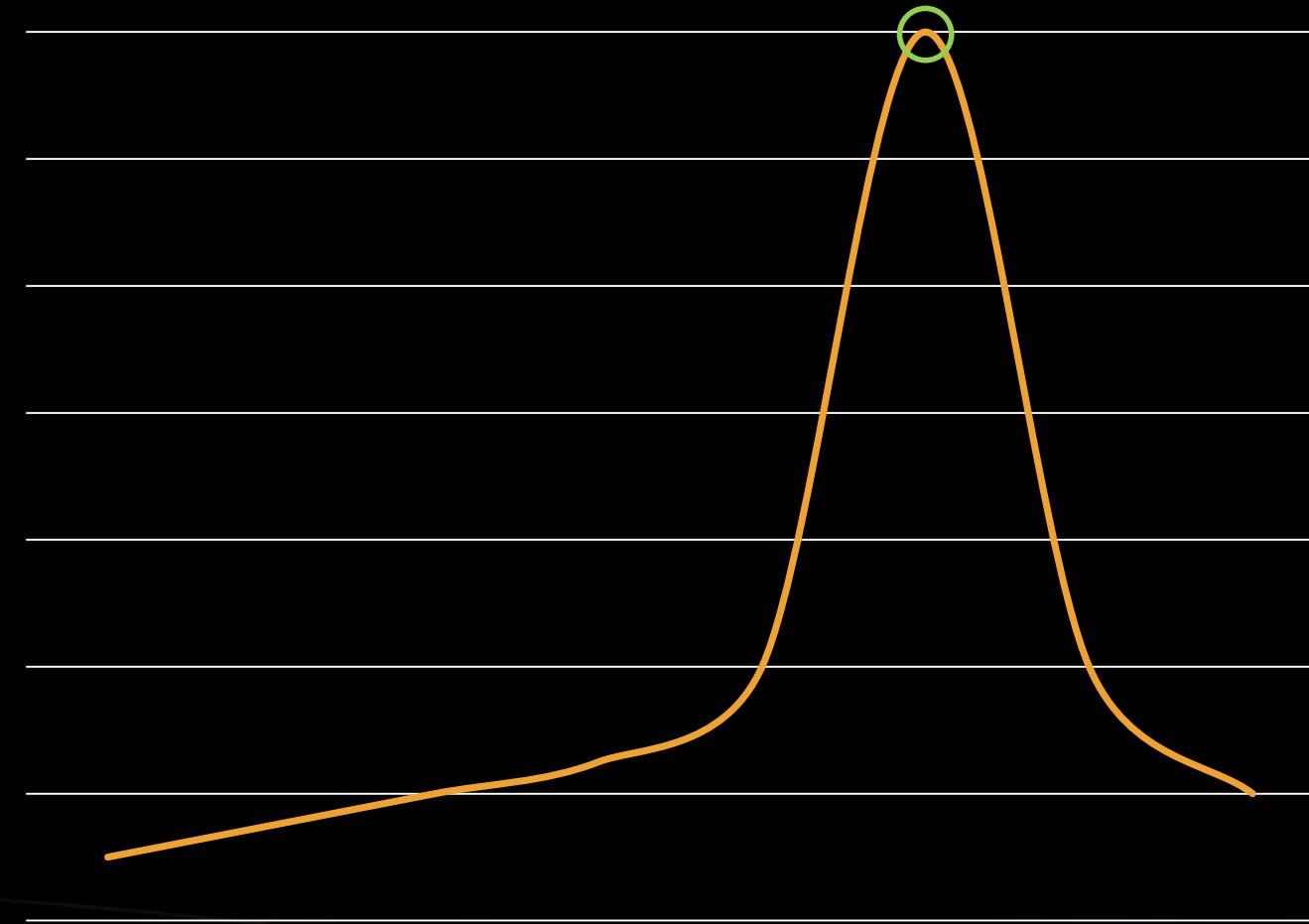
Peak Point Visualization



Peak Point Visualization



Peak Point Visualization





Greedy Algorithm for Sum of Coins

Live Coding Exercise (Lab)



Greedy Failure Cases

Greedy Algorithms Often Fail

Sum of Coins Failure

Target: 18



Actual: 0

Sum of Coins Failure

Target: 18



Actual: 10



Sum of Coins Failure

Target: 18



Actual: 15



Sum of Coins Failure

Target: 18



Actual: 16



Sum of Coins Failure

Target: 18



Actual: 17



Sum of Coins Failure

Target: 18



Actual: 18

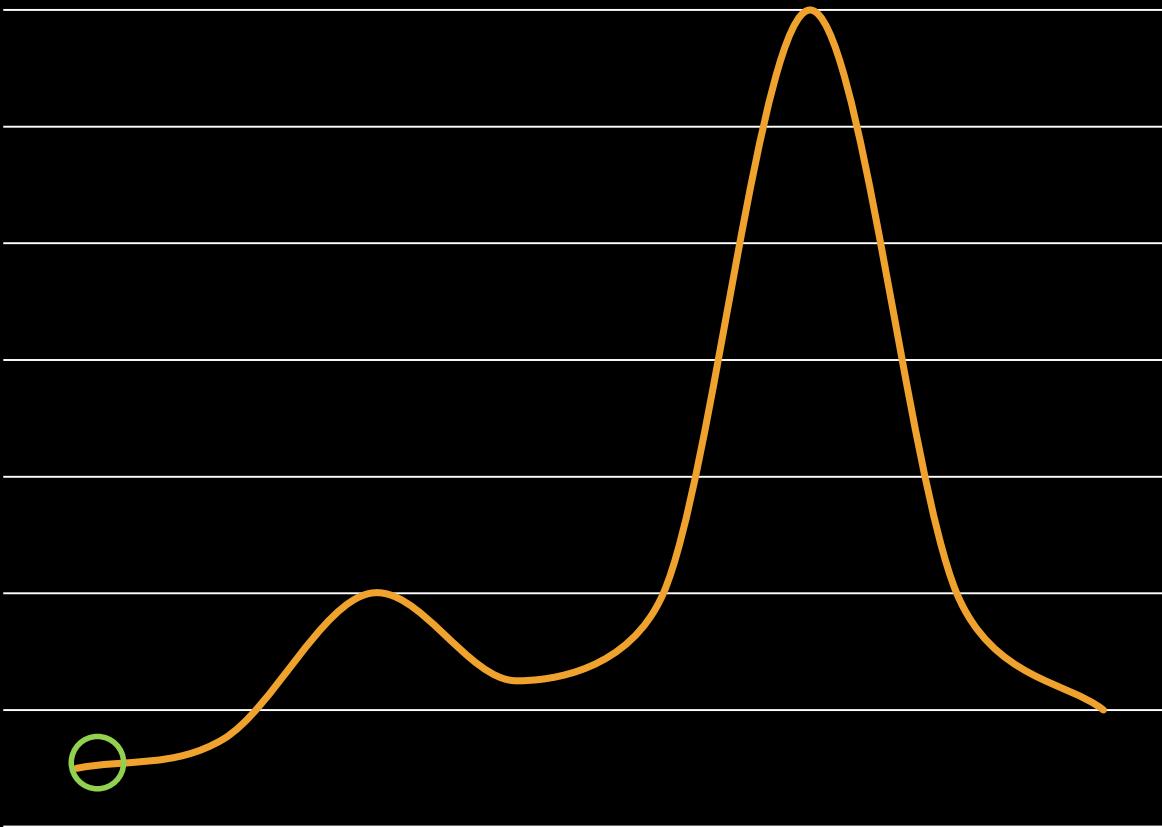


Sum of Coins Failure

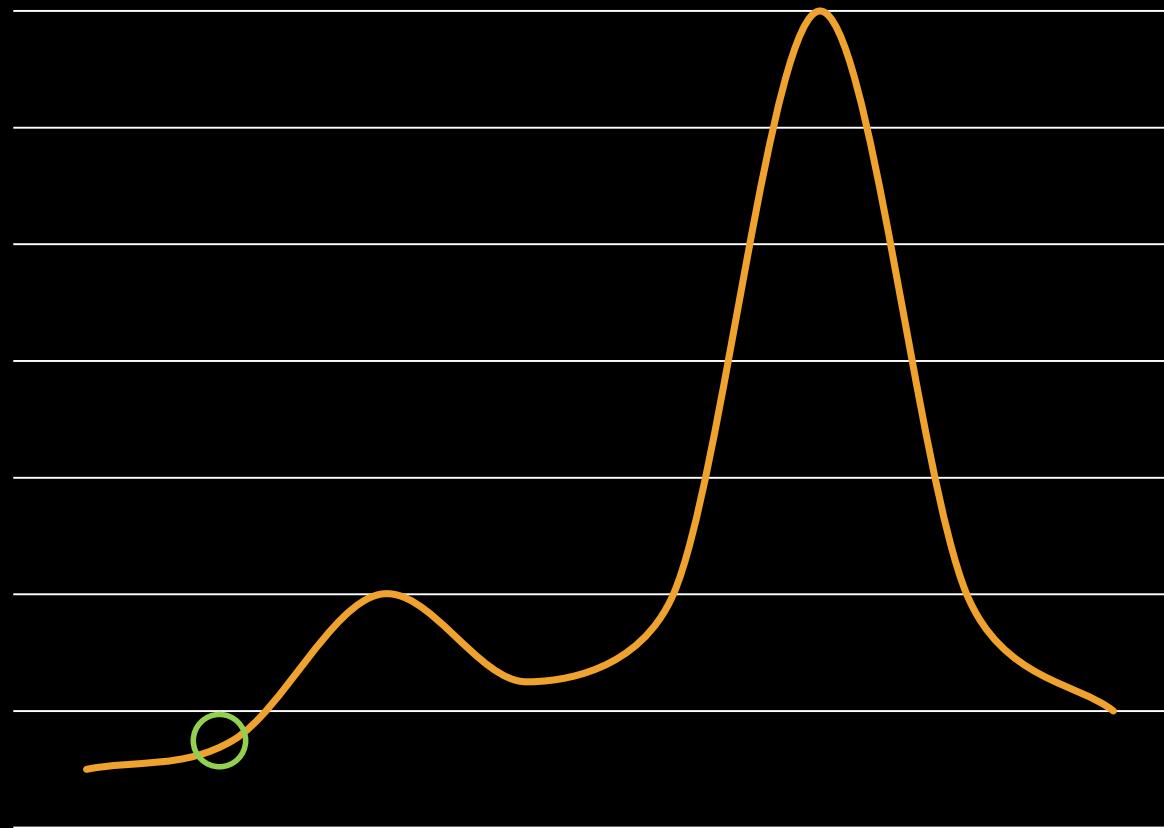
Target: 18



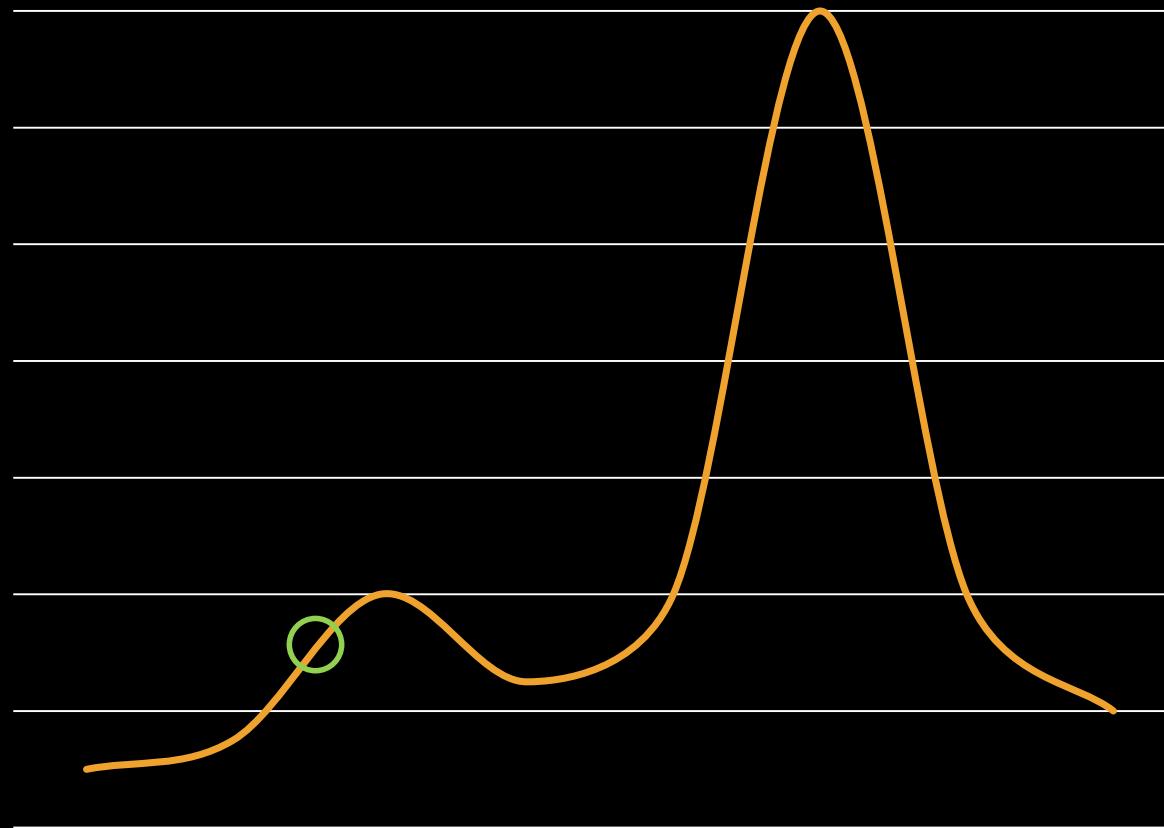
Peak Point Failure



Peak Point Failure



Peak Point Failure

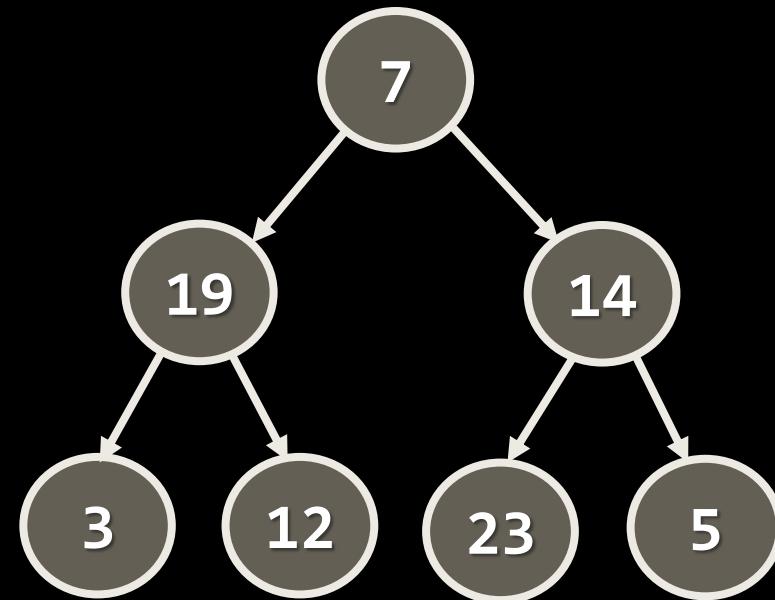


Peak Point Failure



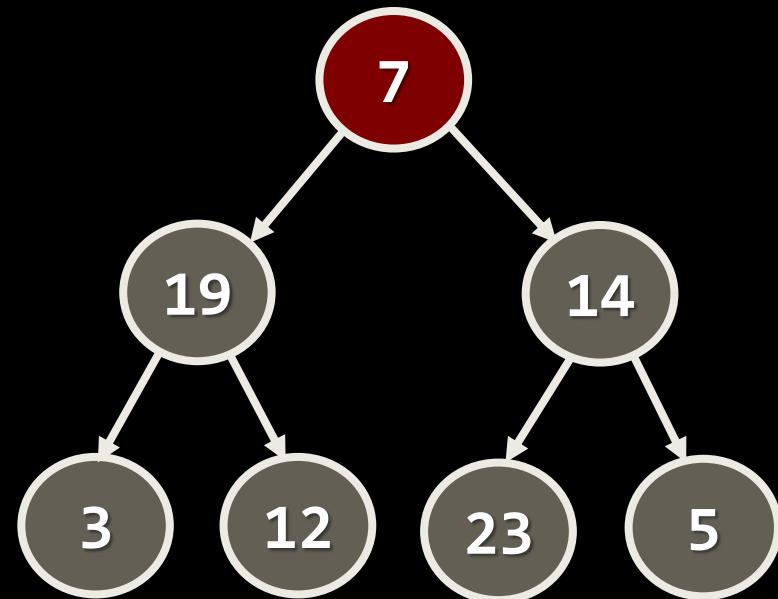
Max Sum Path in Binary Tree

- Largest sum path in a tree (starting at root)
 - Greedy strategy: choose largest next node



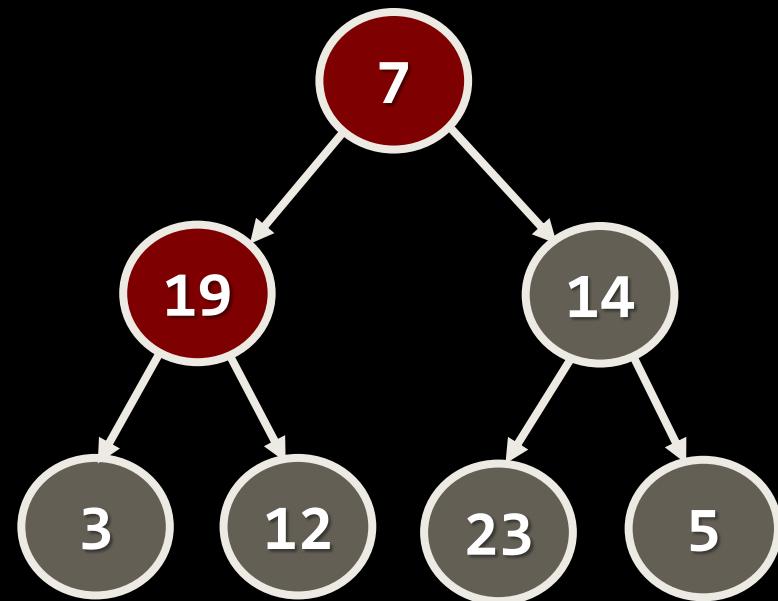
Max Sum in Binary Tree

Sum: 7



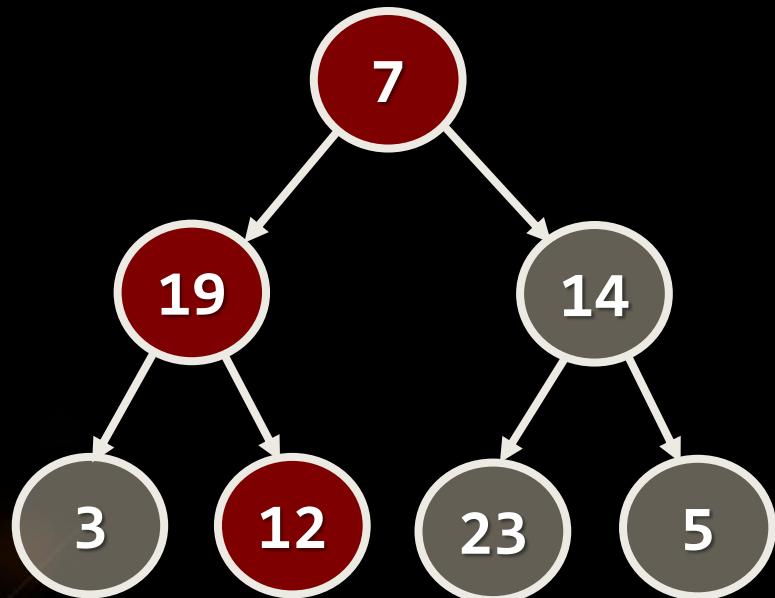
Max Sum in Binary Tree

Sum: 26

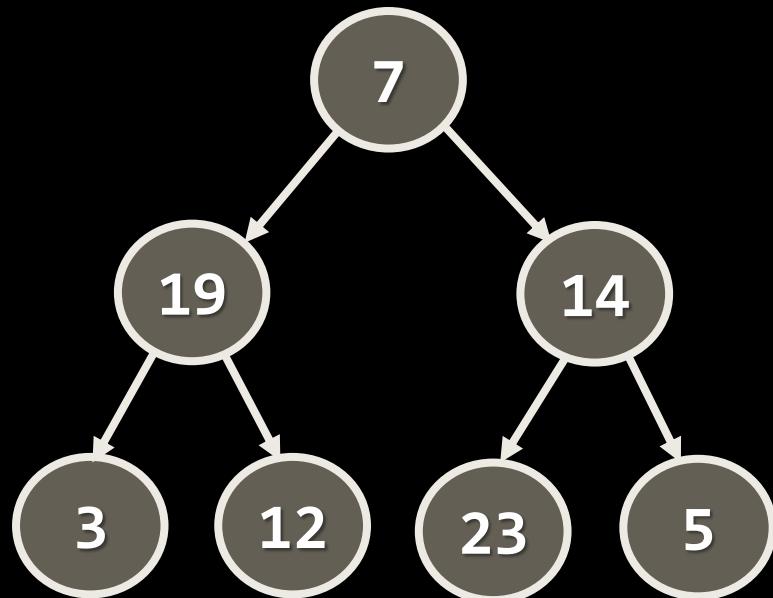


Max Sum in Binary Tree

Sum: 38
Greedy

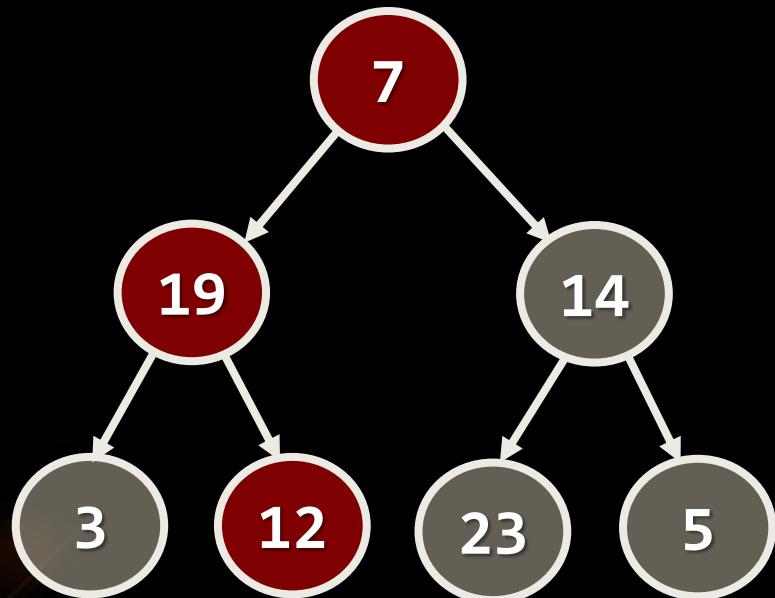


Sum: 0
Actual

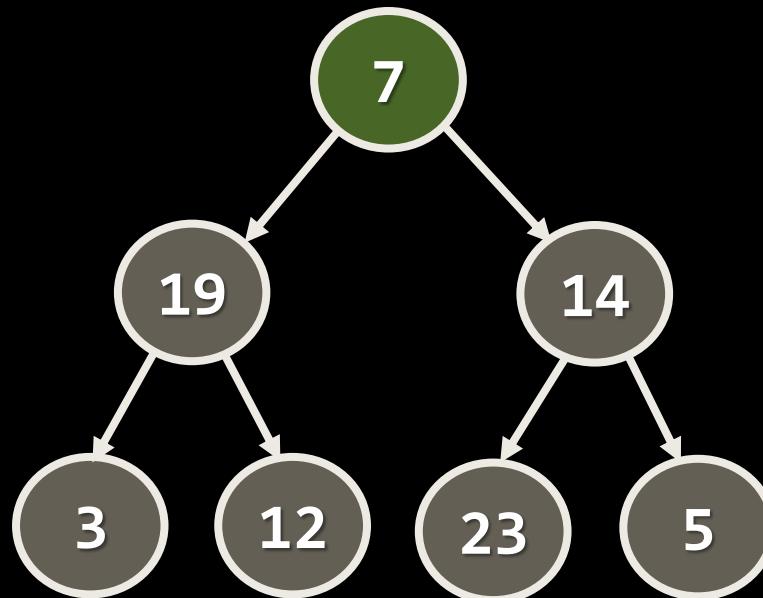


Max Sum in Binary Tree

Sum: 38
Greedy

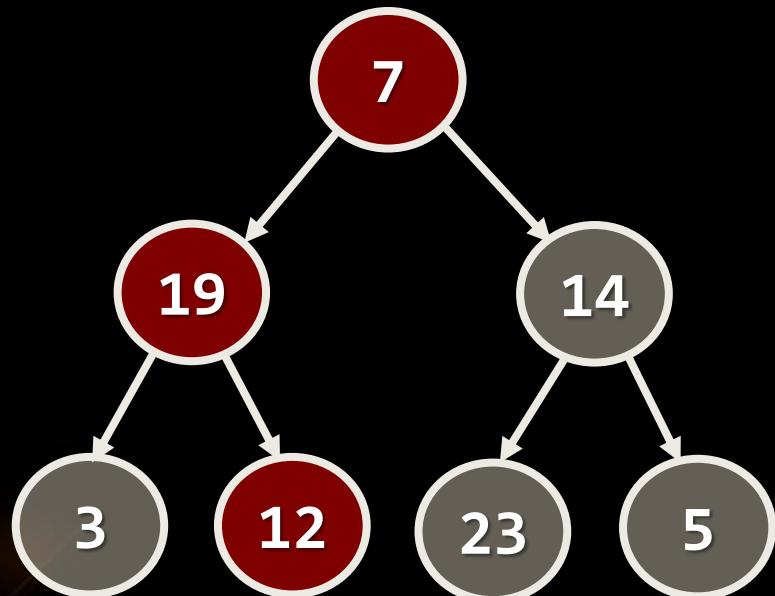


Sum: 7
Actual

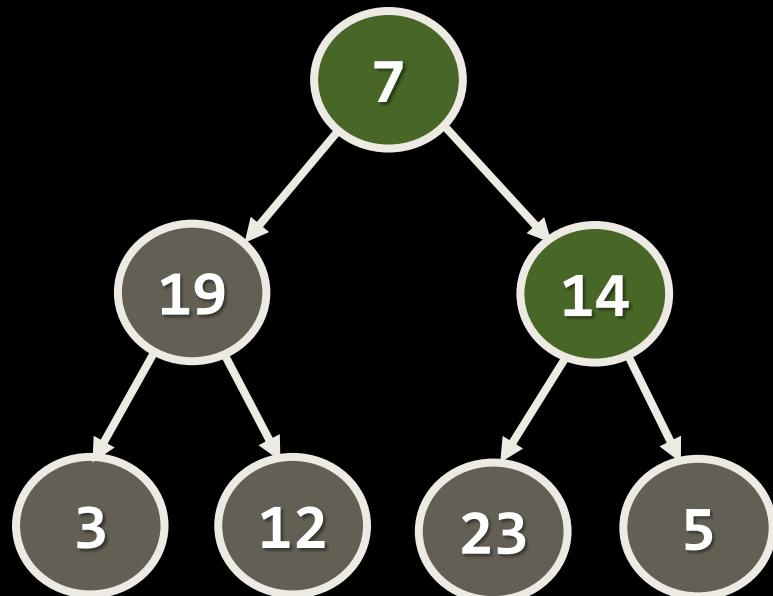


Max Sum in Binary Tree

Sum: 38
Greedy

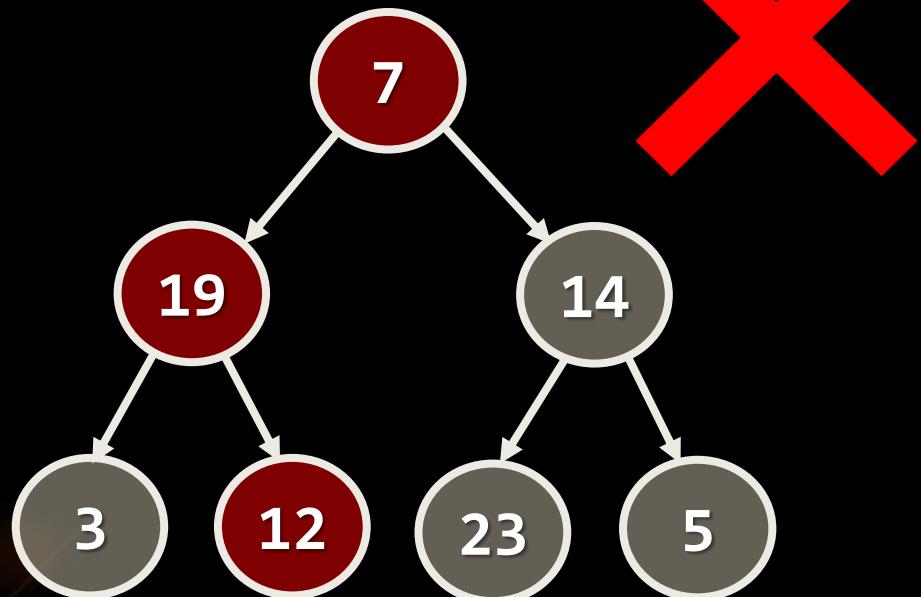


Sum: 21
Actual

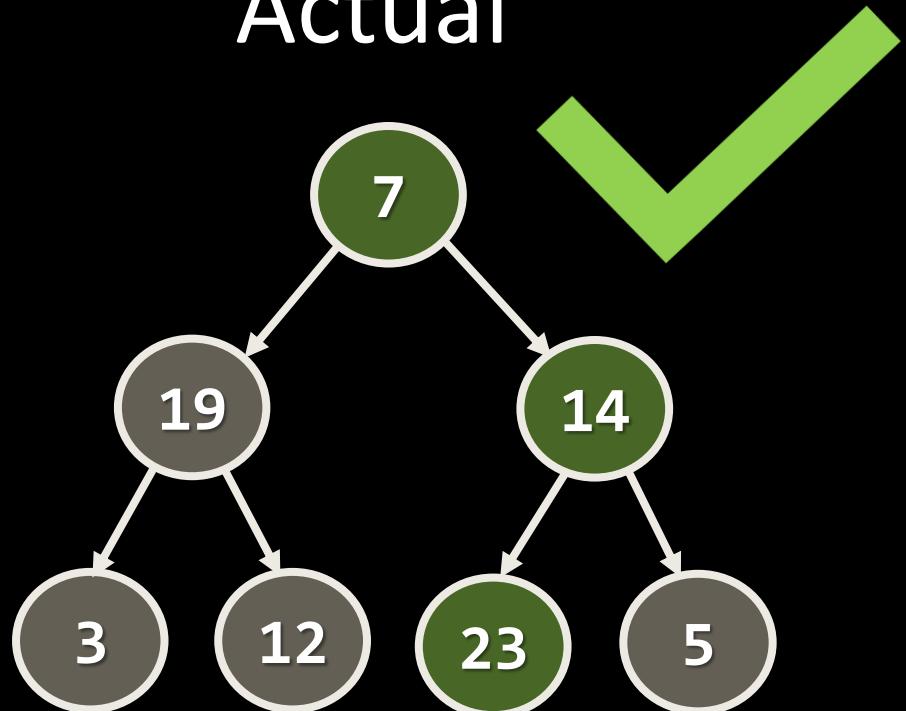


Max Sum in Binary Tree

Sum: 38
Greedy



Sum: 44
Actual





Optimal Greedy Algorithms

Optimal Substructure and Greedy Choice Property

Optimal Greedy Algorithms

- Suitable problems for greedy algorithms have these properties:
 - Greedy choice property
 - Optimal substructure
- Any problem having the above properties is guaranteed to have an optimal greedy solution

Greedy Choice Property

- Greedy choice property
 - A global optimal solution can be obtained by greedily selecting a locally optimal choice
 - Sub-problems that arise are solved by consequent greedy choices
 - Enforced by optimal substructure

Optimal Substructure Property

- Optimal substructure property
 - After each greedy choice the problem remains an optimization problem of the same form as the original problem
 - An optimal global solution contains the optimal solutions of all its sub-problems

Greedy Algorithms: Example

- The "Max Coins" game
 - You are given a set of coins
 - You play against another player, alternating turns
 - Per each turn, you can take up to three coins
 - Your goal is to have as many coins as possible at the end

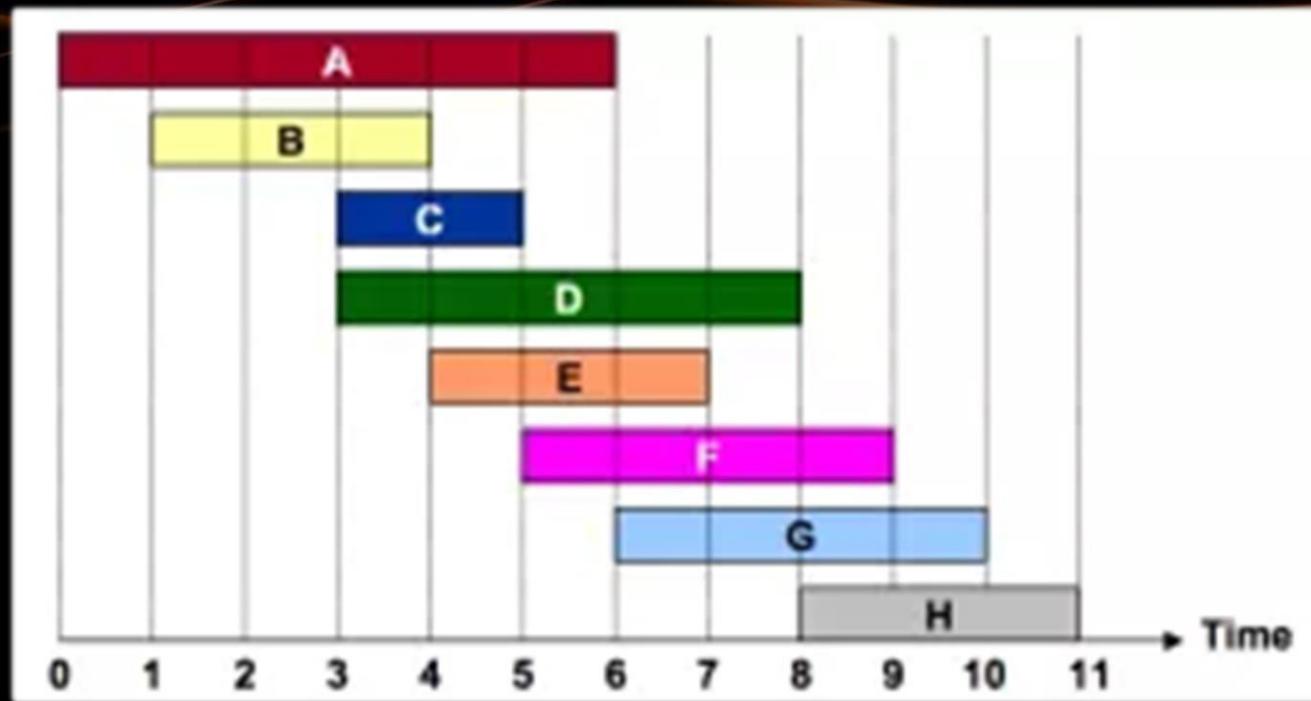


Max Coins – Greedy Algorithm

- A simple greedy strategy exists for the "Max Coins" game

At each turn take the maximum number of coins

- Always choose the local maximum (at each step)
 - You don't consider what the other player does
 - You don't consider your actions' consequences
- The greedy algorithm works optimally here
 - It takes as many coins as possible



Activity Selection Problem

The Greedy Algorithm and Why It Is Optimal

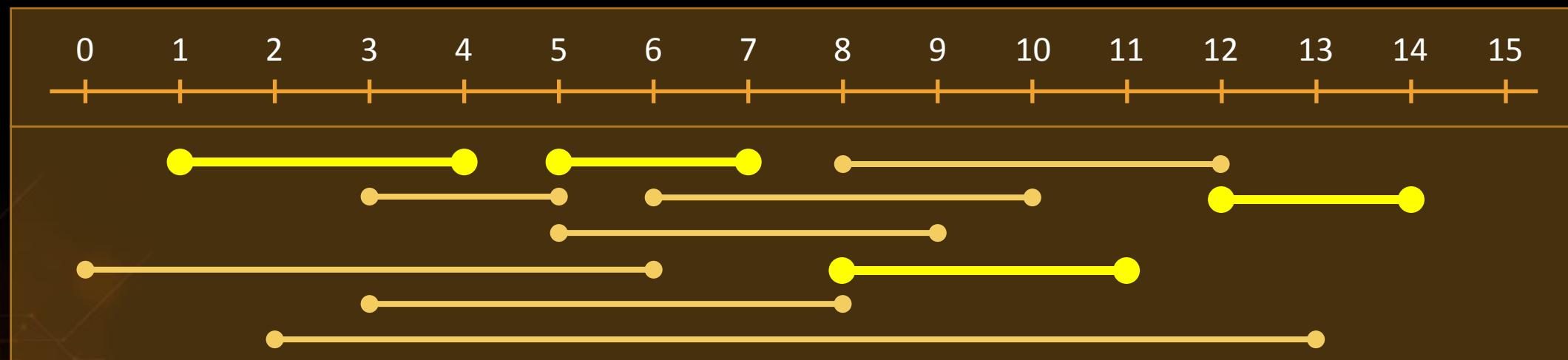
Activity Selection Problem

- The Activity Selection Problem (a.k.a. Conference Scheduling Problem)
 - Given a set of activities $S = \{a_1, a_2, \dots, a_n\}$
 - Each having a start & finish time: $a_i = \{s_i, f_i\}$
 - Activities are "compatible" if they don't overlap
 - i.e. their intervals do not intersect
 - What is the maximum-size subset of compatible activities?
 - i.e. which is the largest list of compatible activities that can be scheduled?

Activity Selection Problem – Example

- Activity selection problem example:

Index	1	2	3	4	5	6	7	8	9	10	11
Start (s_i)	1	3	0	5	3	5	6	8	8	2	12
Finish (f_i)	4	5	6	7	8	9	10	11	12	13	14



- Several optimal solutions: $\{a_1, a_4, a_8, a_{11}\}$, $\{a_2, a_4, a_9, a_{11}\}$, ...

Activity Selection Problem: Greedy

- A greedy algorithm for the Activity Selection Problem:

```
While (S is not empty)
```

```
    Select from S an activity A with the earliest finish
```

```
    Remove A + all activities from S conflicting with A
```

- Greedy characteristics of the above algorithm

- Taking the earliest finish activity gives more time for all others
- We pick an activity preserving the "maximum remaining time"

Activity Selection Problem: Implementation



- Single scan (linear) implementation of the greedy algorithm for the Activity Selection Problem:

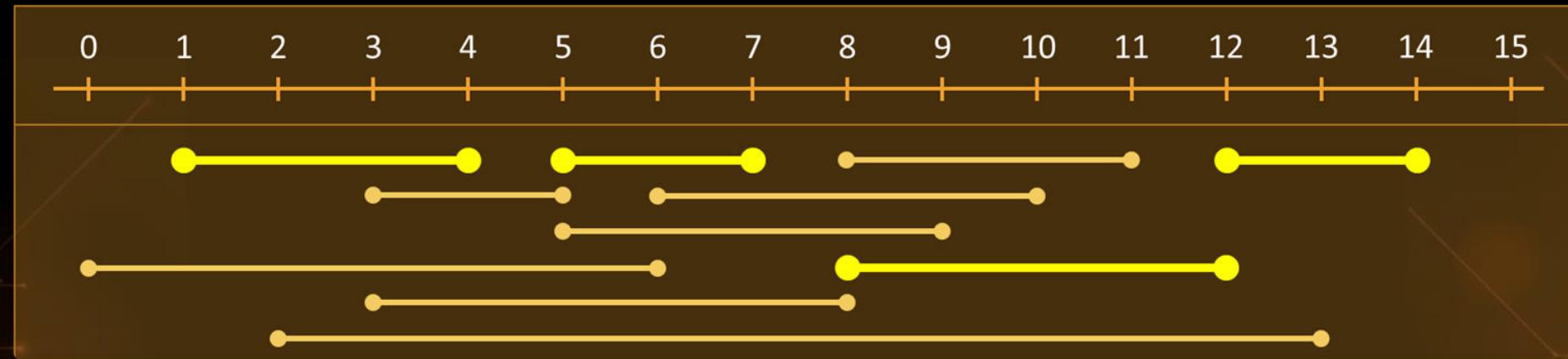
Sort the activities from S by their finish time

```
Last = first activity from S
for ( $a$  in  $S$ )
    if ( $a.Start \geq Last.Finish$ )
        //  $a$  does not conflict with  $Last$ 
        print  $a$ 
    Last =  $a$ 
```

Proving Greedy Optimality

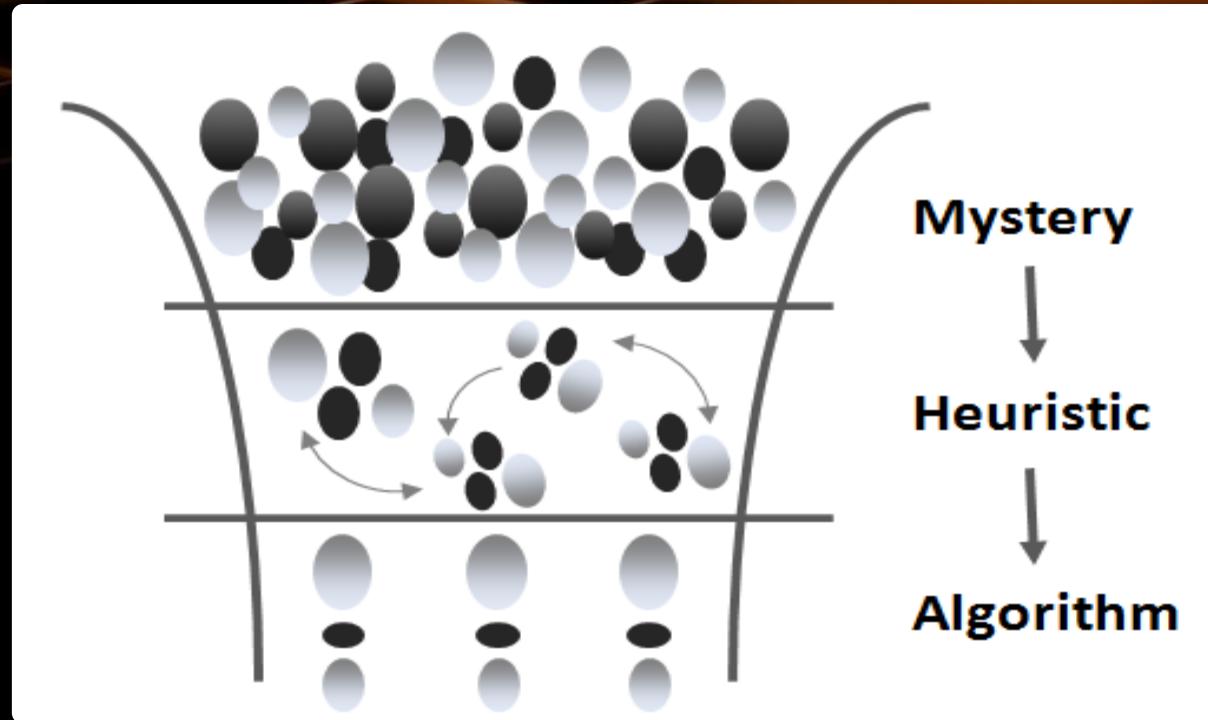
- To prove the discussed greedy is optimal we:
 - Need to prove the problem has a **greedy choice** property
 - Need to prove the problem has **optimal substructure**
- Greedy properties are satisfied:
 - A solution starting with a **greedy choice** exists: the earliest finish
 - **Optimal substructure** exists:
 - If we remove the activity **A** with the earliest finish time activity
 - We reduce the problem to the same problem of smaller size (without activities in **S**, which intersect the activity **A**)

Index	1	2	3	4	5	6	7	8	9	10	11
Start (s_i)	1	3	0	5	3	5	6	8	8	2	12
Finish (f_i)	4	5	6	7	8	9	10	11	12	13	14



Activity Selection Problem

Live Demo

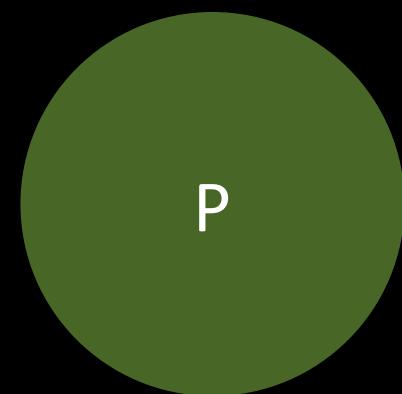


Heuristic Algorithms

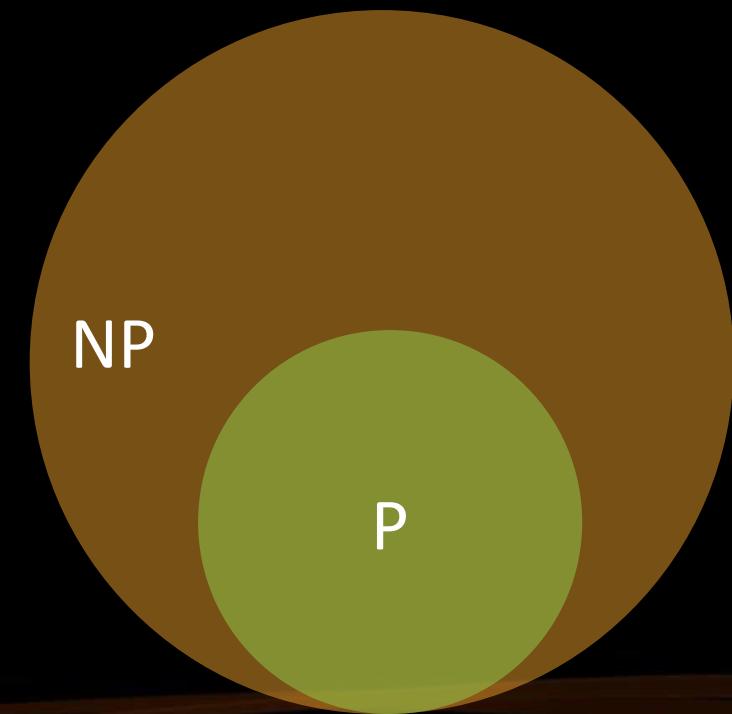
Greedy, Genetic, Branch and Bound

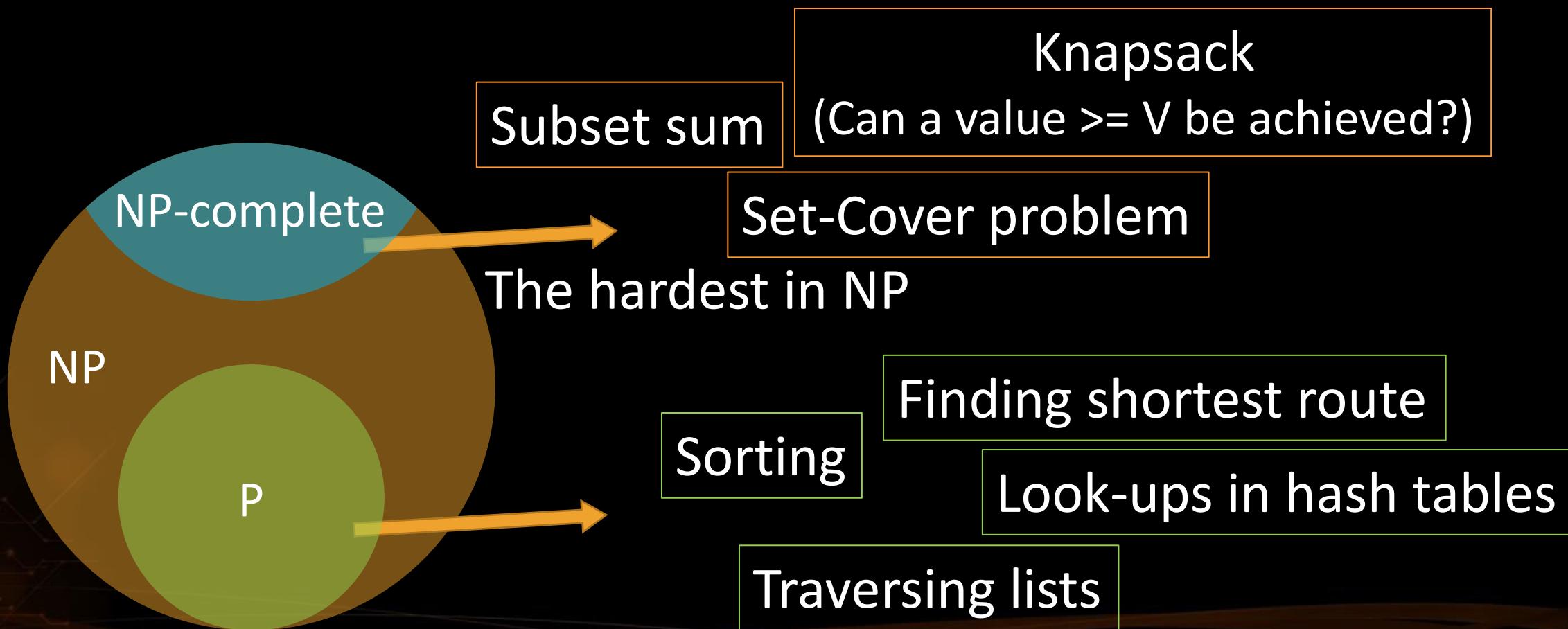
- Some problems are hard to be solved (no fast algorithm exists)
- Heuristic algorithms solve hard problems approximately
 - They find a good solution, but cannot guarantee it is optimal
- Examples of heuristic algorithms:
 - Greedy algorithms – make a greedy choice at each step
 - Genetic algorithms – based on inheritance, mutation, selection, ...
 - Branch and bounds – optimized backtracking with cut-offs
 - Others...

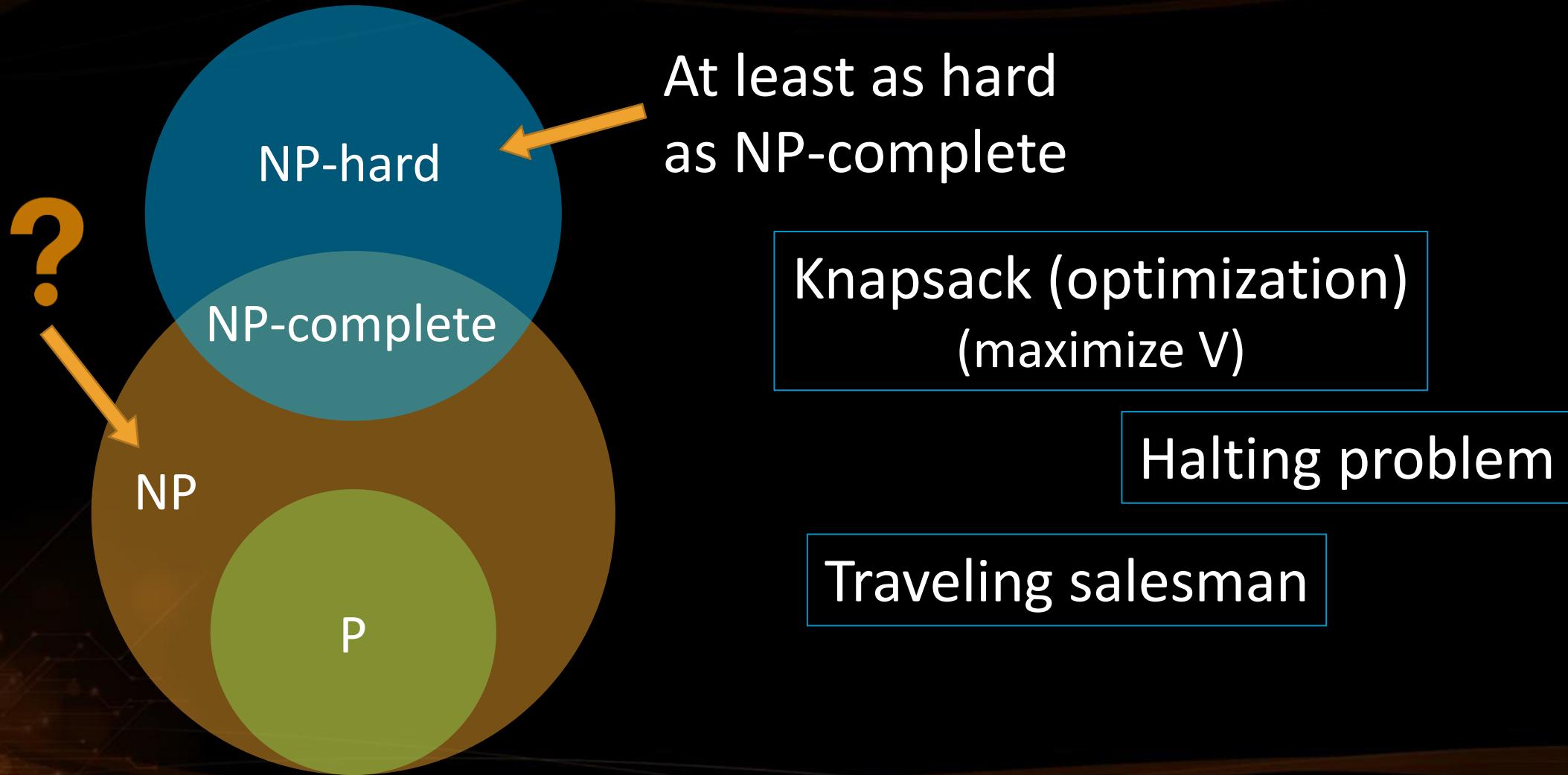
- P - Category in which the algorithms are **solvable** in polynomial time
- Polynomial -> $5N^5 + 3N^4 + N$ is $O(N^5)$
- Not a polynomial -> 2^N



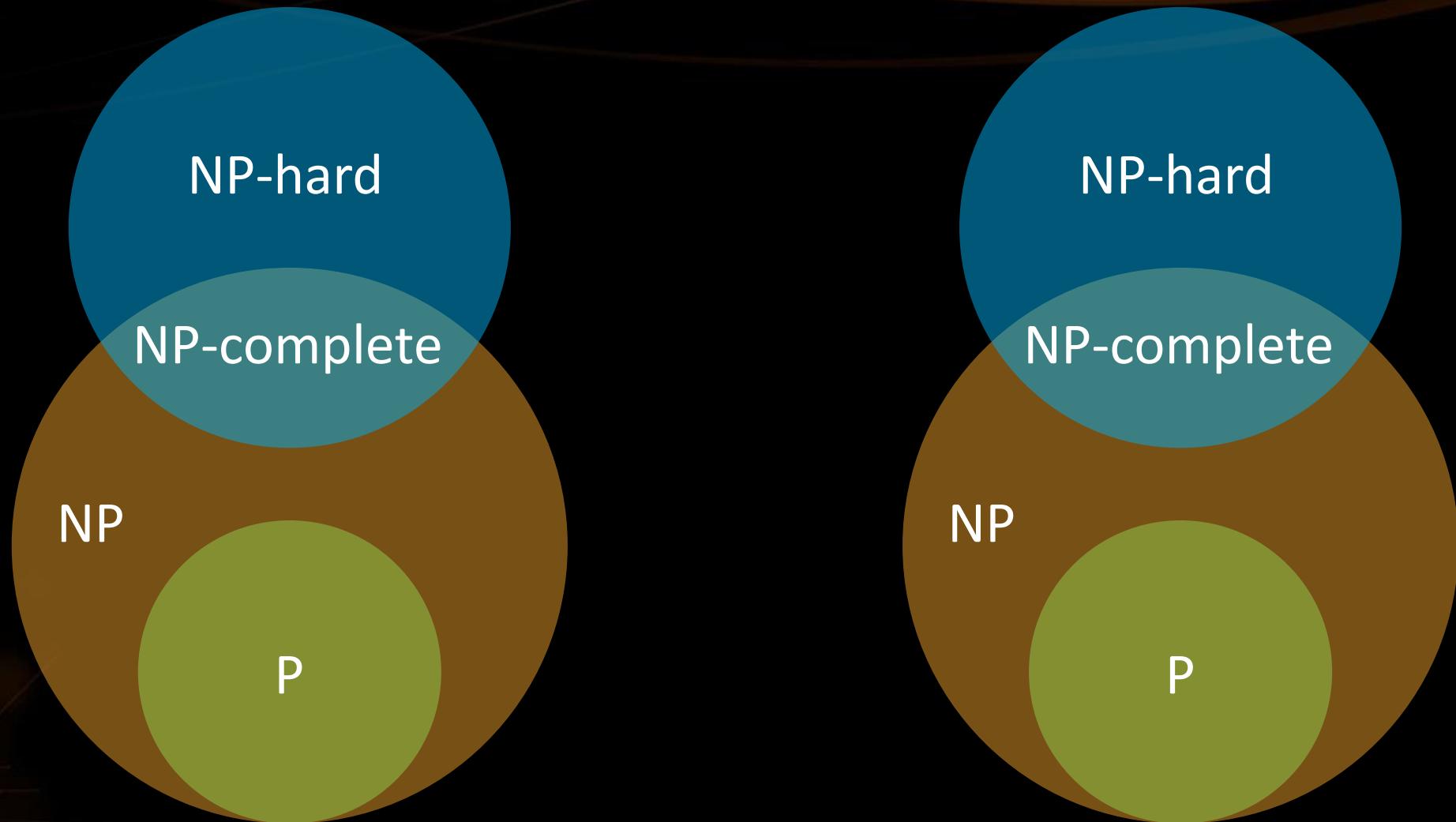
- NP - Category in which the algorithms are **verifiable** in polynomial time.
- Decision problems
- Example:
 - Does a route shorter than L exist?
 - Yes/No



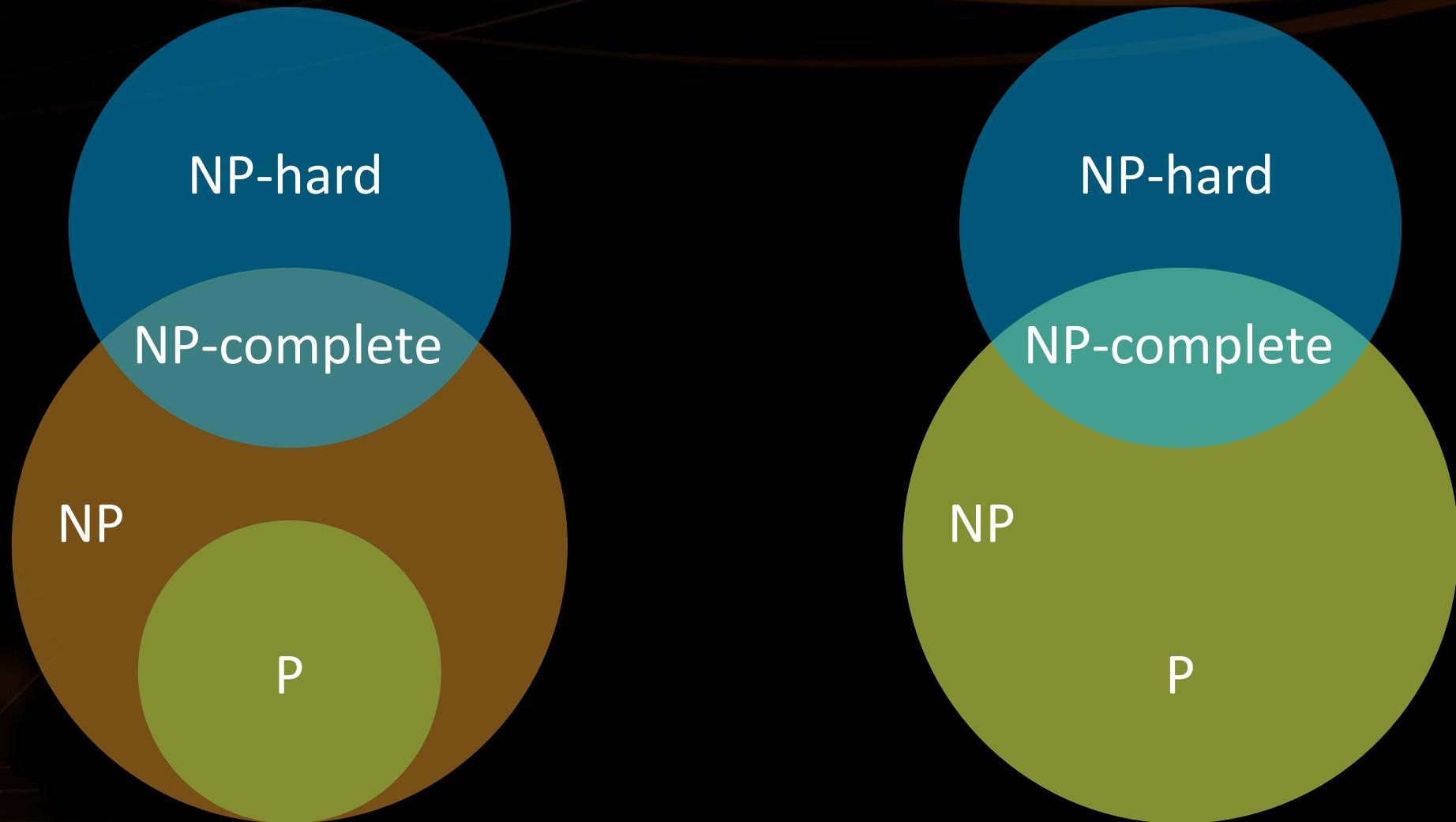




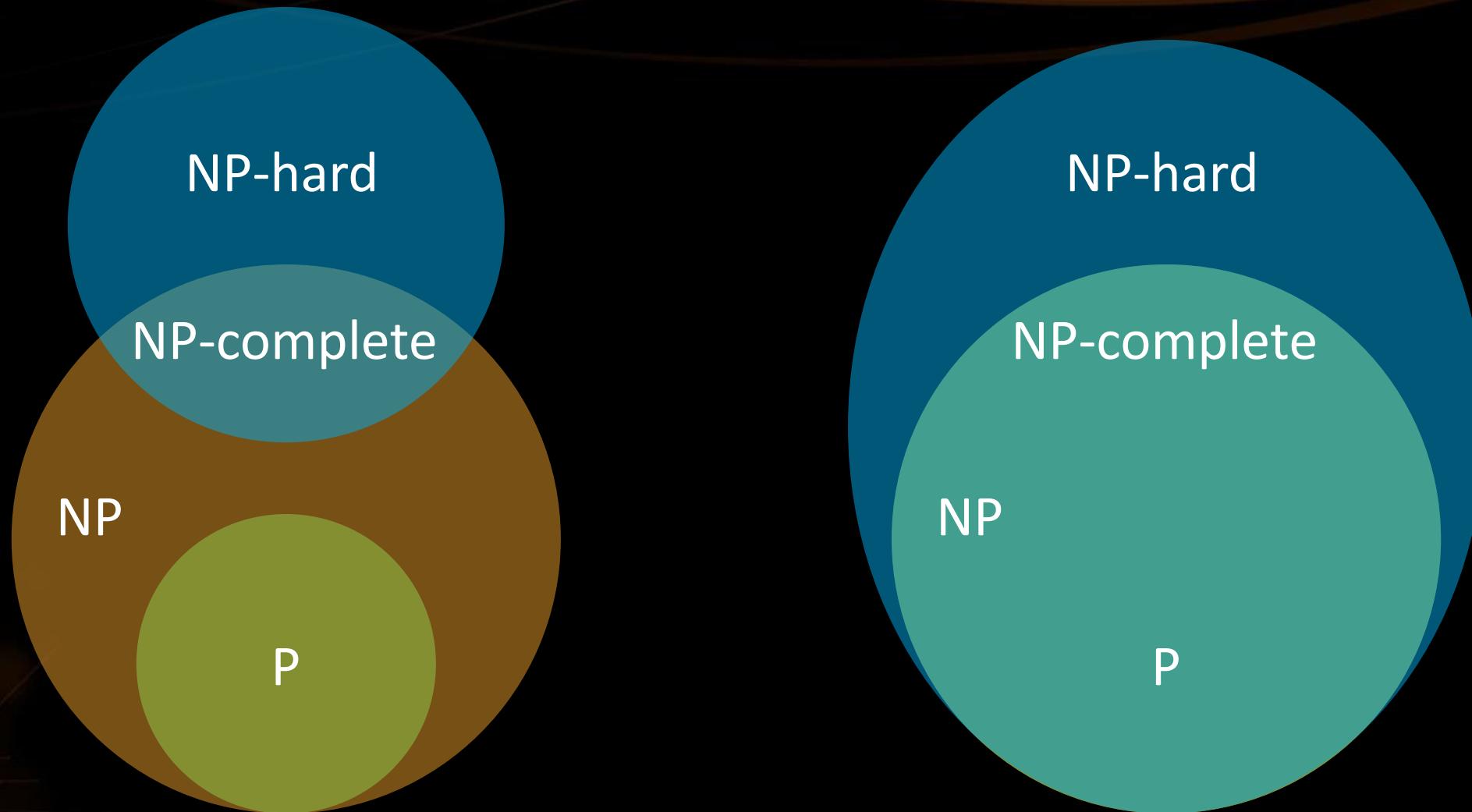
P vs NP



P vs NP

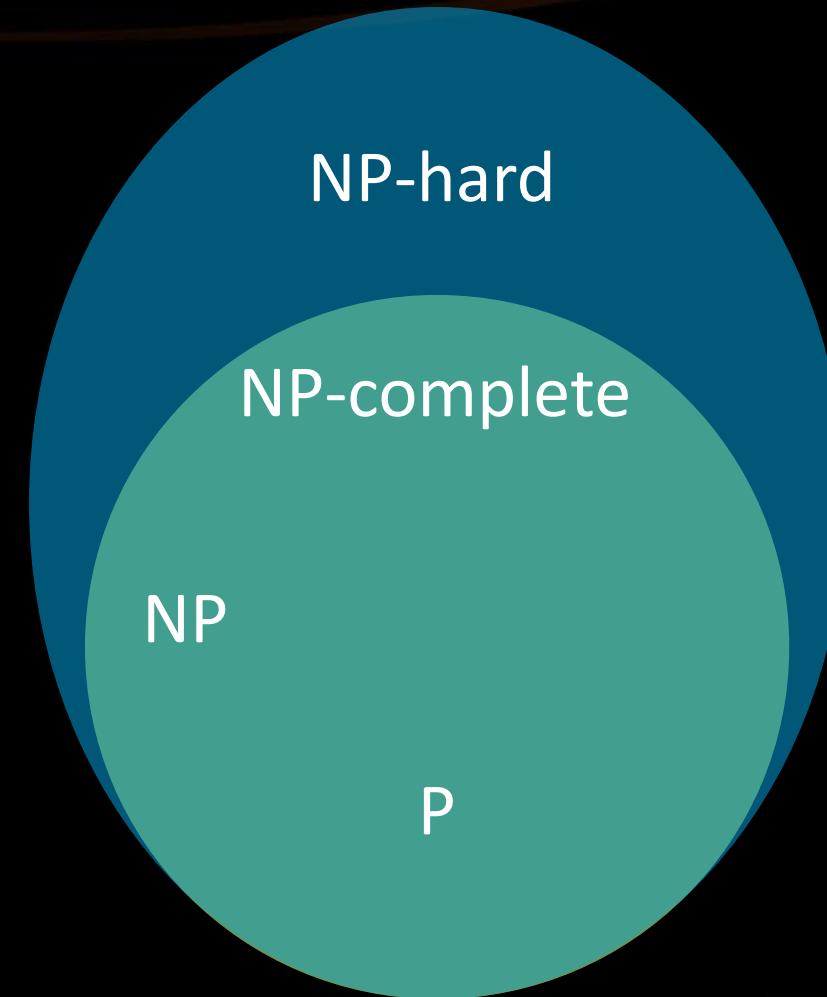


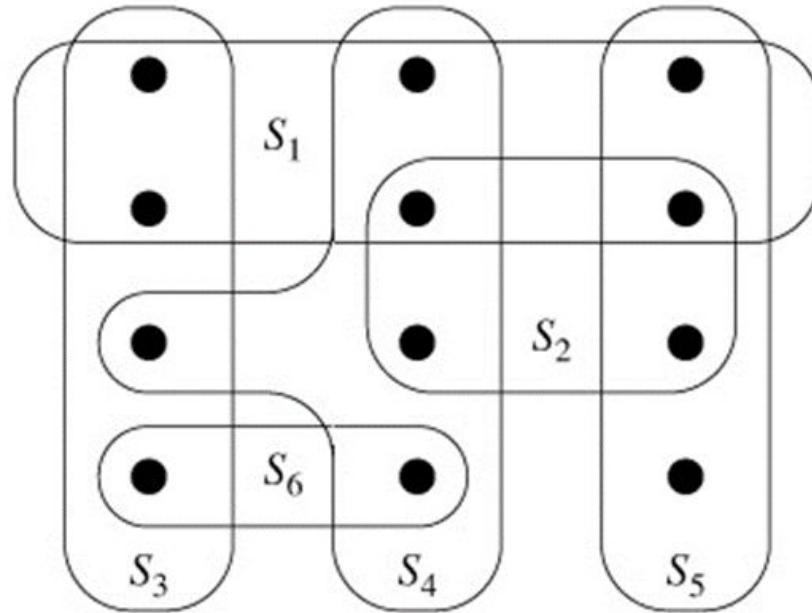
P vs NP



■ Millennium Problem

- Prize of \$1,000,000
- Prove either $P=NP$ or $P \neq NP$
- Currently > 100 attempts





The Set Cover Problem

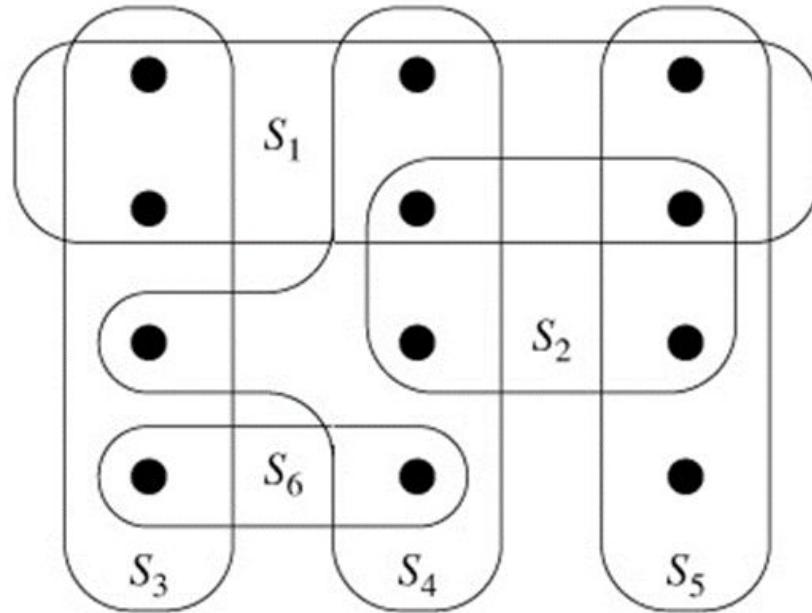
Using Greedy for Approximation

Set Cover Problem

- The Set Cover Problem (SCP) is such a problem
- SCP formulation:
 - Given a set $U=\{1,2,\dots,m\}$ called "the Universe"
 - And a set $S=\{\{\dots\}, \{\dots\}, \{\dots\}, \dots\}$ of n sets whose union = U
 - Find the smallest subset of S , the union of which = U (if it exists)
- Example of SCP:
 - $U = \{1, 2, 3, 4, 5, 6\}$
 - $S = \{ \{1, 3\}, \{1\}, \{2, 4\}, \{2, 5\}, \{2, 6\}, \{2, 3, 6\}, \{4, 6\}, \{4, 5, 6\}, \{6\} \}$

Set Cover Problem

- The SCP turns out very complex!
 - The optimal solution is NP-complete
 - Infeasible for real-world calculations (unless P = NP)
- Good solutions can be achieved through a greedy approach:
 - At each step pick the set containing the largest number of uncovered elements, e. g.
 - $U = \{1, 2, 3, 4, 5, 6\}$
 - $S = \{ \{1, 3\}, \{1\}, \{2, 4\}, \{2, 5\}, \{2, 6\}, \{2, 3, 6\}, \{4, 6\}, \{4, 5, 6\}, \{6\} \}$



The Set Cover Problem

Live Coding Exercise (Lab)

References & Further Reading



- Recommended further reading on greedy algorithms:
 - Lecture @ Boston University (Shang-Hua Teng)
 - www.cs.bu.edu/~steng/teaching/Fall2003/lectures/lecture7.ppt
 - Lecture @ University of Pennsylvania
 - www.cis.upenn.edu/~matuszek/cit594-2005/Lectures/36-greedy.ppt
 - Book on Algorithms @ Berkeley University
 - www.cs.berkeley.edu/~vazirani/algorithms/chap5.pdf
 - Book "Programming = ++ Algorithms;" – Chapter 9
 - www.programirane.org

Summary

- Greedy algorithms make local optimal decision at each step and expect to achieve the global optimal solution
- Greedy algorithms give optimal solution for problems holding:
 - Greedy choice & optimal substructure
- Heuristic algorithms give approximation
 - Not always the optimal solution



Greedy Algorithms



Questions?

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