

Algorithms and Programming

Lecture 10 – Problem solving methods (I)

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Course content

Programming in the large

Programming in the small

- Introduction in the software development process
- Procedural programming
- Modular programming
- Abstract data types
- Software development principles
- Testing and debugging
- Recursion
- Complexity of algorithms
- Search and sorting algorithms
- Problem solving methods
 - Generate and test, Backtracking
 - Divide et impera

Last time

- Search
 - Sequential seach
 - Binary search

- Sort
 - Selection sort
 - Insert sort
 - Bubble sort
 - Quick sort

Today

- Problem solving methods
 - Types
 - Techniques
 - Exact methods
 - Heuristic methods
 - Algorithms
 - Backtracking
 - Divide and conquer

Problem solving methods

- Strategies for solving difficult problems
- General algorithms that can be applied to solve certain type of problem (the problem needs to satisfy certain required criteria)

- Problem characteristics
 - Structure
 - Number of solutions
 - Search, optimization, simulation, etc

Problem types

By structure

- Problems that can be divided in sub-problems
 e.g. search for an element in a list
- Problems that can not be divided in sub-problems e.g. place queens on a chessboard

By number of solutions

- Problems with a single solution
 e.g. sort a list
- Problems with several solutions e.g. generate permutations

By solving possibilities

- Problems that can be deterministically solved
 e.g. compute the sin or the square root of a number
- Problems that can be solved stochastically (heuristics)
 e.g. Real-world problems such as vehicle routing optimization
 Need to search for a solution

Problem types

By run time complexity

- Problems from class P can be solved in polynomial time (n², n³,...)
 e.g. sorting problems
- Problems from class NP can not be solved in polynomial time (n!, 2ⁿ,...)
 e.g. the shortest path in a graph of cities

By scope

- Search / optimization problems e.g. planning, scheduling, resource allocation
- Modeling problems
 e.g. forecasting, classification, prediction
- Simulation e.g. economic game theory

Problem solving

- Identification of a solution
 - Computer science search process
 - Engineering and mathematics optimization process

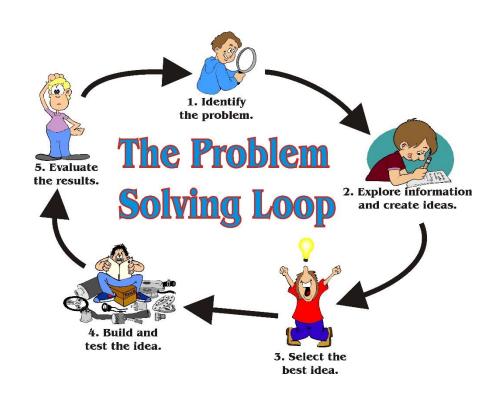
- How?
 - Representation of (partial) solutions points in the search space
 - Design of search operators transform a possible solution in a new solution

The problem solving loop

Problem definition

Problem analysis

- Choose problem solving technique
 - Search
 - Knowledge representation
 - Abstraction



Problem solving steps

- Choose a problem solving technique
 - Solve using rules (and a control strategy) to move in the search space until a path from the initial state to the final one is identified
 - Solve using search
 - Sistematically analyse states in order to identify:
 - A path from initial state to the final one
 - An optimal state
 - Search space all possible states and the operators that allow moving from a state to another
 - How to choose the search strategy?
 - Computational complexity (run time and space)
 - Completeness the algorithm always ends and finds a solution if one exists
 - Optimality the algorithm finds the optimal solution

Problem solving by search

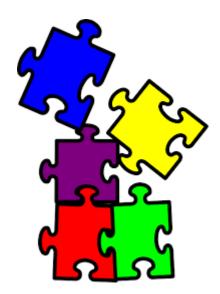
- Many search strategies how to choose one?
 - Computational complexity
 - Performance depends on:
 - Time needed to run the algorithm
 - Space (memory) needed for the run
 - Size of the input data
 - Computer speed
 - Processor quality

- Internal factors
- External factors
- Measured using complexity Computational Efficiency
 - **Space** memory needed to identify the solution
 - **S(n)** quantity of memory used by the best algorithm A which solves a decision problem f with input data of size n
 - **Time** time needed to identify the solution
 - **T(n)** running time (number of steps) used by the best algorithm A for a decision problem f with input data of size n

Problem solving by search

- Solving problems by search can mean:
 - Build the solution step by step

Identify the potential optimal solution



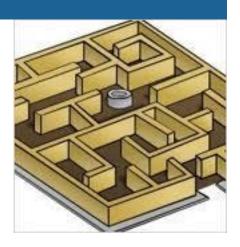
Problem solving by search

- Solving problems by search using standard methods
 - Exact methods
 - Generate and test
 - Backtracking
 - Divide and conquer
 - Dynamic programming
 - Heuristic methods
 - Greedy method

- Basic idea
 - Generate a possible solution and verify if it's correct
 - Trial and error
 - Exhaustive search



- Generate: determine all possible solutions
- Test: search solutions that are correct (satisfy some conditions)
- When to use it?
 - Problems that can have multiple solutions
 - Problems with restrictions (solutions need to satisfy some conditions)



Algorithm

```
#D = D(D1) = D(D1(D2))...
def generate_test(D):
    while (True):
        sol = generate_solution()
        if (test(sol) == True):
            return sol
```

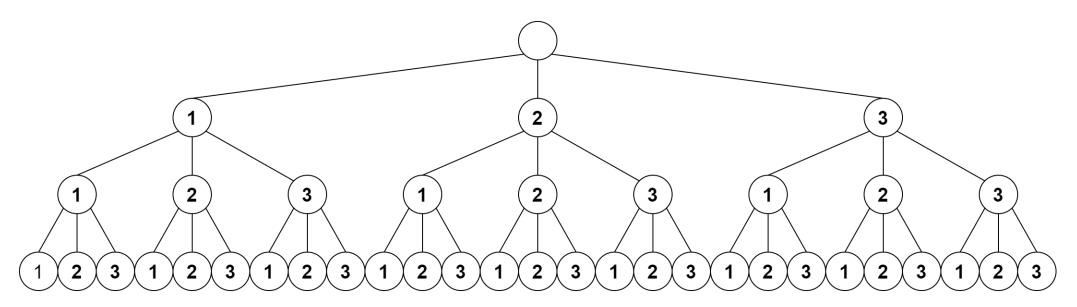
- 1. Generate a possible solution
- 2. Test is solution is correct
- 3. Quit if a solution is found, return to step 1 otherwise
- > This is not backtracking

• Example: generate permutations with n=3 elements

[1, 2, 3] [1, 3, 2] [2, 1, 3] [2, 3, 1] [3, 1, 2] [3, 2, 1]

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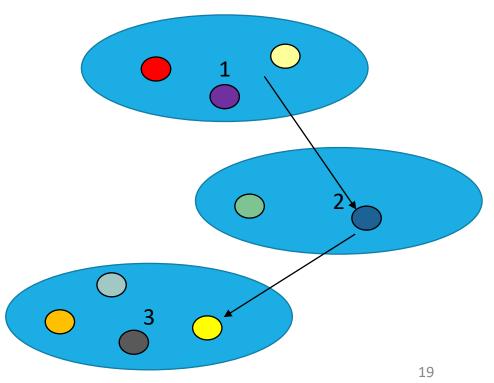
- Example: generate permutations with n=3 elements
- Complexity
 - Number of possible solutions: 3³ (which is nⁿ)



- Possible improvements
 - Do not explore all possible solutions
 - Example: when i= 1 there is no point to verify j=1 and k=1 because this can not lead to a possible solution
 - Build (partially) correct solutions
 - That satisfy certain conditions

```
#D = D(D1) = D(D1(D2))...
def generate_test(D):
    while (True):
        sol = generate_solution_cond()
        if (test(sol) == True):
            return sol
```

- Brute-force technique for finding solutions, with the main characteristic that it has the ability to undo – backtrack – when a potential solution is not valid
- Basic idea:
 - Try every possibility to see if it's a solution
 - unless we already know it's not valid
 - Sequence of choices
 - Once a choice is selected....another choice
 - If bad choice => backtrack
 - Until the solution is perfectly valid



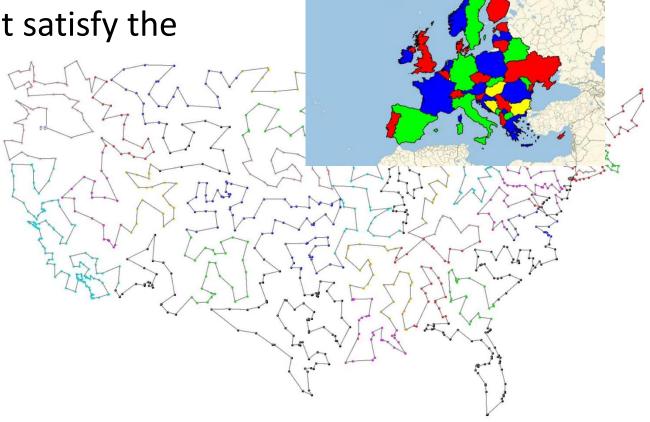
Problems with many candidate solutions

Many of these solutions do not satisfy the

given constraints

• Examples of problems:

- N-Queens Problem
- Sudoku
- K-colouring maps of (n regions)
- Traveling Salesperson Problem



- Search space of a solution s is S (definition domain)
- A solution is formed of several elements s[0], s[1], s[2],...
- init: function that generates an empty value for the definition domain of the solution
- getNext: function that returns the next element from the definition domain
- isConsistent: function that verifies if a (partial) solution is consistent
- *isSolution:* function that verifies if a (partial) solution is a final (complete) solution of the problem

Backtracking: Iterative version

Generate permutations with n elements

```
def init():
    return 0
def getNext(sol, pos):
    return sol[pos] + 1
def isConsistent(sol):
    isCons = True
    i = 0
    while (i<len(sol)-1) and (isCons==True):</pre>
        if (sol[i] == sol[len(sol) - 1]):
            isCons = False
        else:
            i = i + 1
    return isCons
def isSolution(solution, n):
    return len(solution) == n
```

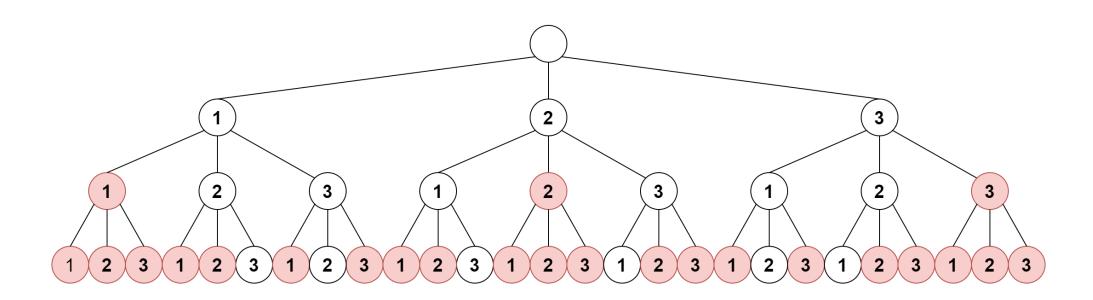
```
def permut back(n):
    k = 0; solution = []
    initValue = init()
    solution.append(initValue)
    while (k >= 0):
        isSelected = False
        while (isSelected==False) and (solution[k]<n):</pre>
            solution[k] = getNext(solution, k)
            isSelected = isConsistent(solution)
        if (isSelected == True):
            if (isSolution(solution,n) == True):
                yield solution
            else:
                k = k + 1
                solution.append(init())
        else:
            del(solution[k])
            k = k - 1
def callPermut():
    for p in permut back(3):
        print(p)
callPermut()
```

Backtracking: Recursive version

Generate permutations with n elements

```
def init():
                                                def permut_back_rec(n, solution):
    return 0
                                                    initValue = init()
                                                    solution.append(initValue)
def getNext(sol, pos):
                                                    elem = getNext(solution, len(solution) - 1)
    return sol[pos] + 1
                                                    while (elem <= n):</pre>
                                                        solution[len(solution) - 1] = elem
                                                        if (isConsistent(solution) == True):
def isConsistent(sol):
                                                            if (isSolution(solution, n) == True):
    isCons = True
    i = 0
                                                                vield solution
    while (i<len(sol)-1) and (isCons==True):</pre>
                                                            else:
        if (sol[i] == sol[len(sol) - 1]):
                                                                yield from permut back rec(n, solution[:])
            isCons = False
                                                        elem = getNext(solution, len(solution) - 1)
        else:
            i = i + 1
                                                def callPermutRec():
    return isCons
                                                    for p in permut back rec(3, []):
                                                        print(p)
def isSolution(solution, n):
    return len(solution) == n
                                                callPermutRec()
```

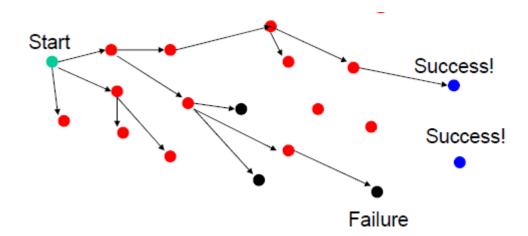
• Nodes explored for generating permutations with n=3 elements



Recap: How to use backtracking

- Represent the solution as a vector: s[0], s[1], s[2],...
- Define what a valid solution candidate is

(filter out candidates that will not lead to a solution)



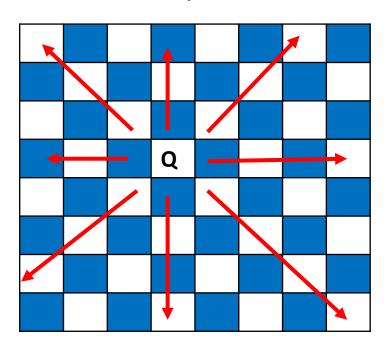
Remember:

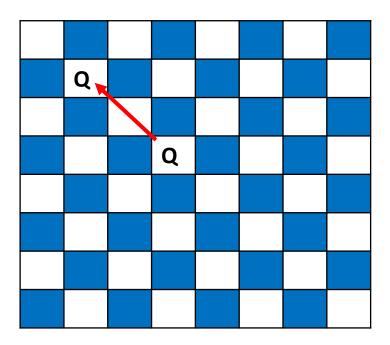
- Problem space: states (nodes) and actions (paths that lead to new states)
- If a node leads to failure go back and try other alternatives

Backtracking: Example

8 queens

- 8 queens
 - Classic backtracking problem
 - Place 8 queens on an 8x8 chessboard so that no queen can attack another





Backtracking: Example

8 queens

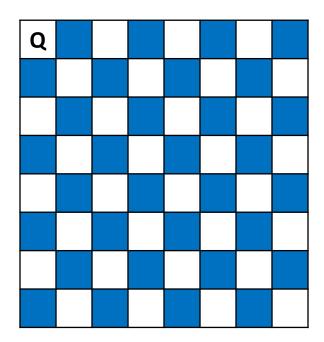
- 8x8 chessboard => 64 locations
 - After placing one queen => 63 locations to choose from
 -
 - 64*63*62*61*60*59*58*57 = 178,462,987,637,760 possibilities

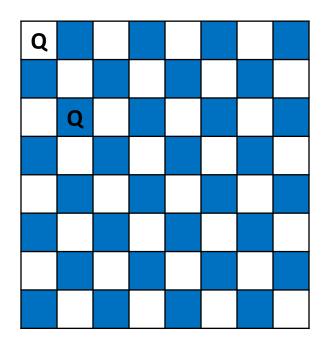
- However:
 - A valid solution has:
 - exactly 1 queen in each row and exactly 1 queen in each column
 - Explore 1 queen per column (not per cell)
 - Possibilities reduced to 8⁸ = 16,777,216

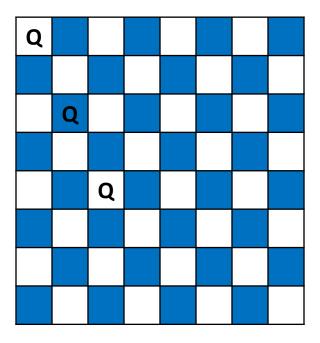
Backtracking: Example

8 queens

- Make a choice for first column
- The second choice is affected by the first choice, etc







Backtracking: Example N queens

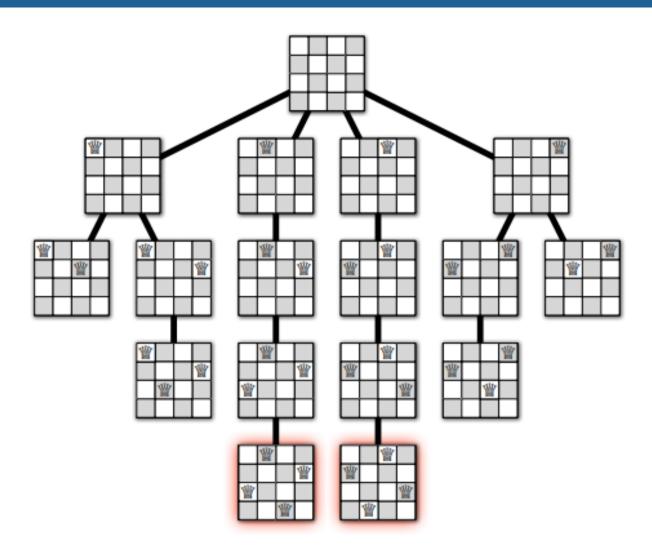
```
def isConsistent(solution, row, column):
    # check the row
    for j in range(column):
        if solution[row][j] == 1:
            return False
    # check the first diagonal to left (up)
    for i,j in zip(range(row,-1,-1), range(column,-1,-1))
        if solution[i][j] == 1:
            return False
    # check the second diagonal to left (down)
    i = row + 1
    j = column - 1
    while (i < len(solution)) and (j >= 0):
        if solution[i][j] == 1:
            return False
        i = i + 1
        j = j - 1
    return True
```

```
def initSolution():
    solution = [[0 for i in range(n)] for j in range(n)]
    return solution

def printSolution(solution):
    for row in solution:
        print(row)
```

```
def solveProblem(solution, column):
    if column >= n:
        print("COMPLETE solution:")
        printSolution(solution)
        return True
    for i in range(n):
        if isConsistent(solution, i, column):
            solution[i][column] = 1
            print("Partial correct solution:")
            printSolution(solution)
            if solveProblem(solution, column + 1) == True:
                return True
            else:
                solution[i][column] = 0
    return False
n=8
solveProblem(sol, 0)
```

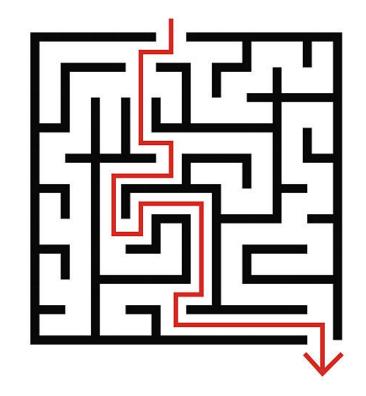
Backtracking Example

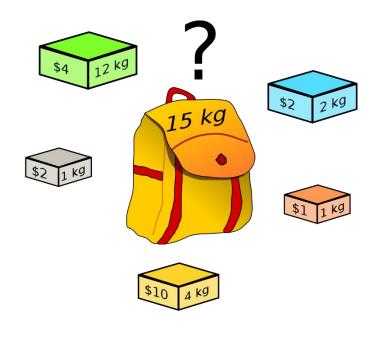


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Backtracking: other examples

5	3			7				
5 6			1	9	5			
	9	8					6	
8				6				3
8 4 7			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9





- Basic idea
 - Divide the problem in several independent sub-problems similar to the initial problem but smaller in size and determine the final solution by combining sub-solutions
- Mechanism
 - Divide: breaking the problem in sub-problems
 - Conquer: solve the sub-problems
 - Combine: combine sub-solutions to obtain final solution
- When it can be used
 - A problem P with the input data D can be solved by solving the same problem
 P but with input data d, where d < D

Algorithm

```
#D = d1 U d2 U d3...U dn
def div_imp(D):
    if (size(D) < lim):
        return rez
    rez1 = div_imp(d1)
    rez2 = div_imp(d2)
    ...
    rezn = div_imp(dn)
    return combine(rez1, rez2, ..., rezn)</pre>
```

- Example: find the maximum of a list
 - Size of problem = n
 - First version
 - Size of sub-problem 1 = n-1
 - Size of sub-problem 2 = n-2
 - ...
 - meaning:
 - D = I = [11,12,...,ln]
 - d1=[l2,..,ln]
 - d2=[l3,..,ln]
 - ...
 - O(n)

```
def findMax(1):
   Descr: finds the maximum elem of a list
   Input: a list
   Output: the maximum elem of list
   if (len(l) == 1):
       return 1[0]
   max = findMax(1[1:])
   if (max > 1[0]):
        return max
   else:
        return 1[0]
def test findMax():
    assert findMax([2,5,3,6,1]) == 6
    assert findMax([12,5,3,2,1]) == 12
    assert findMax([2,5,3,6,11]) == 11
test_findMax()
```

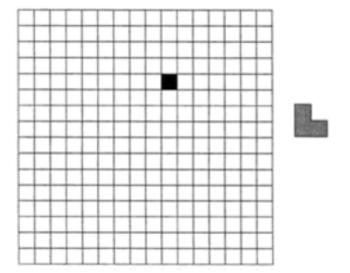
- Example: find the maximum of a list
 - Size of problem = n
 - Second version
 - Size of sub-problem 1 = n/2
 - Size of sub-problem 2 = n/2
 - meaning:
 - D = I = [11,12,...,ln]
 - d1=[l2,..,ln/2]
 - d2=[ln/2+1,..,ln]

• O(n)

```
def findMax_v2(1):
    Descr: finds the maximum elem of a list
    Data: a list
    Res: the maximal elem of list
    if (len(1) == 1):
        return 1[0]
    middle = len(1) // 2
    max left = findMax v2(1[0:middle])
    max right = findMax v2(1[middle:len(1)])
    if (max_left < max_right):</pre>
        return max right
    else:
        return max_left
def test findMax v2():
    assert findMax_v2([2,5,3,6,1]) == 6
    assert findMax_v2([12,5,3,2,1]) == 12
    assert findMax_v2([2,5,3,6,11]) == 11
test findMax v2()
```

Divide et impera – Example

- Consider a chessboard of size 2^m (with 2^m X 2^m cells) that contains a hole (one random cell is removed)
- We have several shapes L
- Objective: cover the chessboard with L shapes (any orientation)



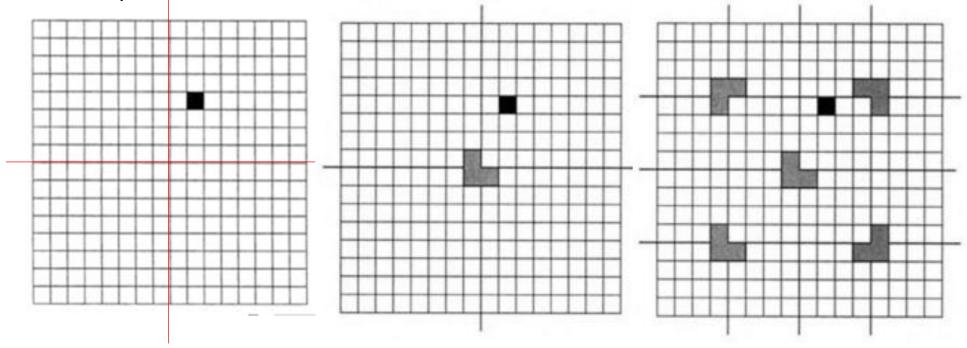
m=4 => chessboard16 X 16

- ✓ Search space: possible arrangements of L shapes on the board
- ✓ D&C is an ideal method

Divide et impera – Example

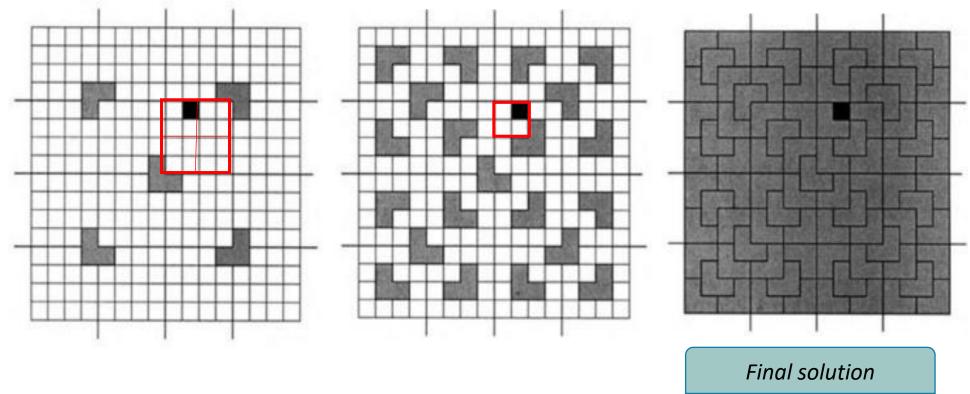
- Divide the chessboard in 4 equal zones
- Only one will contain the hole

Place an L shape such that it covers 3 zones (not the one with the hole)



Divide et impera – Example

• Each square has a single black cell



Recap today

Problem solving methods

- Generate and test
 - Exhaustive
 - Backtracking
- Divide and conquer

Next time

- Algorithms
 - Dynamic programming
 - Greedy method

Reading materials and useful links

- 1. The Python Programming Language https://www.python.org/
- 2. The Python Standard Library https://docs.python.org/3/library/index.html
- 3. The Python Tutorial https://docs.python.org/3/tutorial/
- 4. M. Frentiu, H.F. Pop, Fundamentals of Programming, Cluj University Press, 2006.
- MIT OpenCourseWare, Introduction to Computer Science and Programming in Python, https://ocw.mit.edu, 2016.
- K. Beck, Test Driven Development: By Example. Addison-Wesley Longman, 2002. http://en.wikipedia.org/wiki/Test-driven_development
- 7. M. Fowler, Refactoring. Improving the Design of Existing Code, Addison-Wesley, 1999. http://refactoring.com/catalog/index.html