Heuristics & Metaheuristics for Optimization & Learning

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Optimization & Complexity

[M. Pavone et al., "Metaheuristics for Combinatorial Optimization", Advances in Intelligent Systems and Computing, 2021]

Every day each of us continually makes decisions during own daily activities

Decisions must be taken quickly and effectively

Making decision is very often challenging, and complex

- Large number of information
- Uncertainty
- Dynamicity
- Time Constraints

Optimization & Complexity

[M. Pavone et al., "Metaheuristics for Combinatorial Optimization", Advances in Intelligent Systems and Computing, 2021]

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Making the most rational decision

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Optimization & Complexity

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Making the most rational decision

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Making decision is very often challenging, and complex

Optimizing

Large number of information

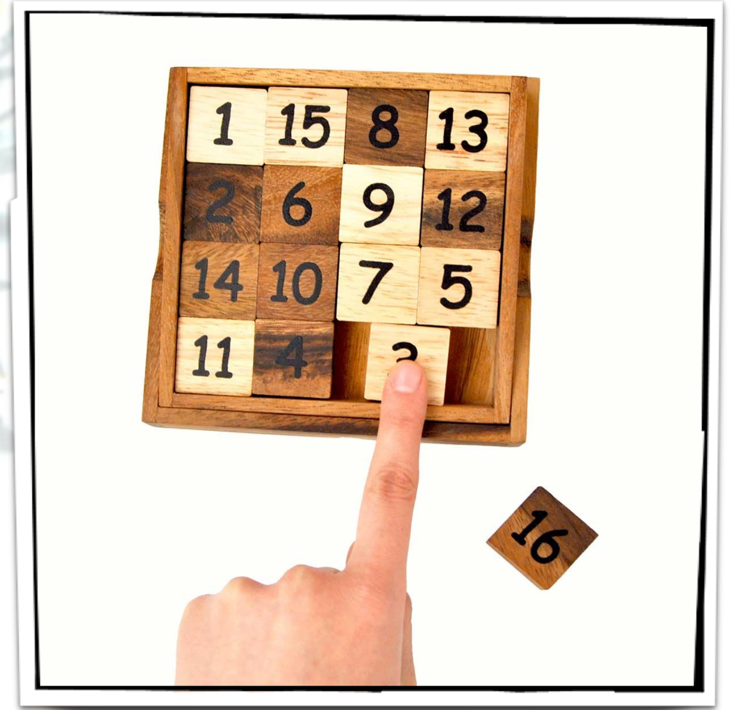
Uncertainty

Dynamicity

Time Constraints

Real-Life Examples

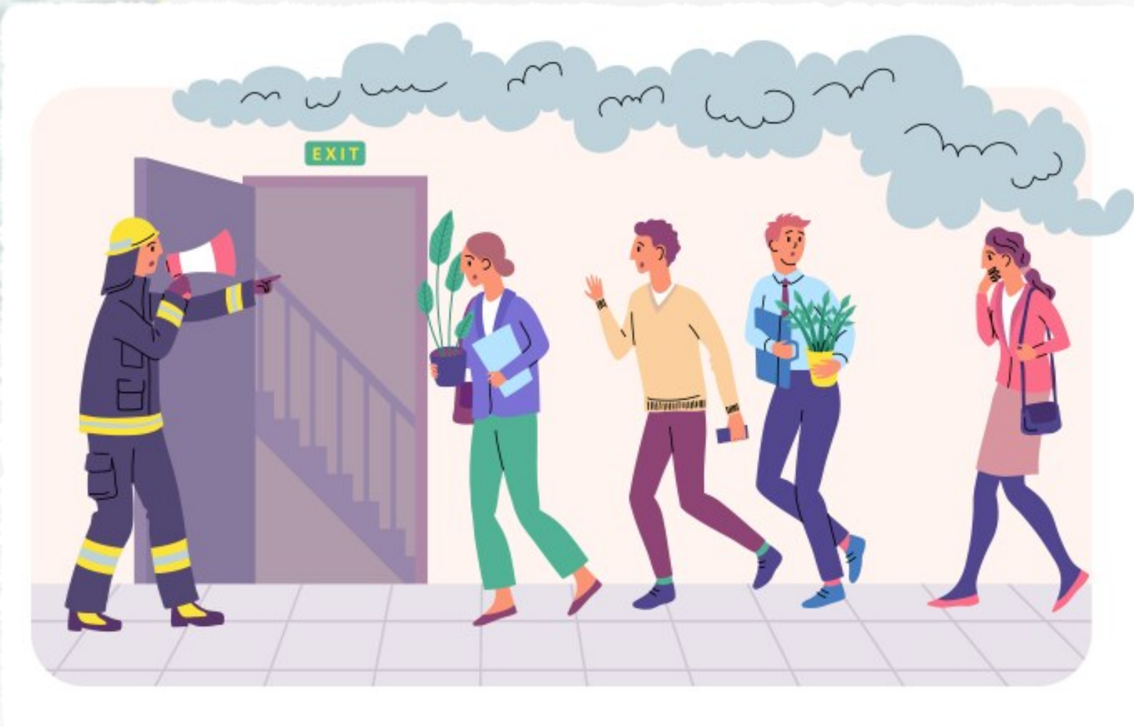
Examples



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

Examples

Examples



Examples

547
489

YEE
GBR
PARIS 2024

WINNERS
LEAGUE
FINAL KYIV 2018
CHAMPIONS LEAGUE

Coneshe ancesions

optimization: an example

The 8-puzzle problem consists of a 3×3 grid containing eight tiles, numbered one through eight.

One of the grid segments (called the ``blank'') is empty. A tile can be moved into the blank position from a position adjacent to it, thus creating a blank in the tile's original position.

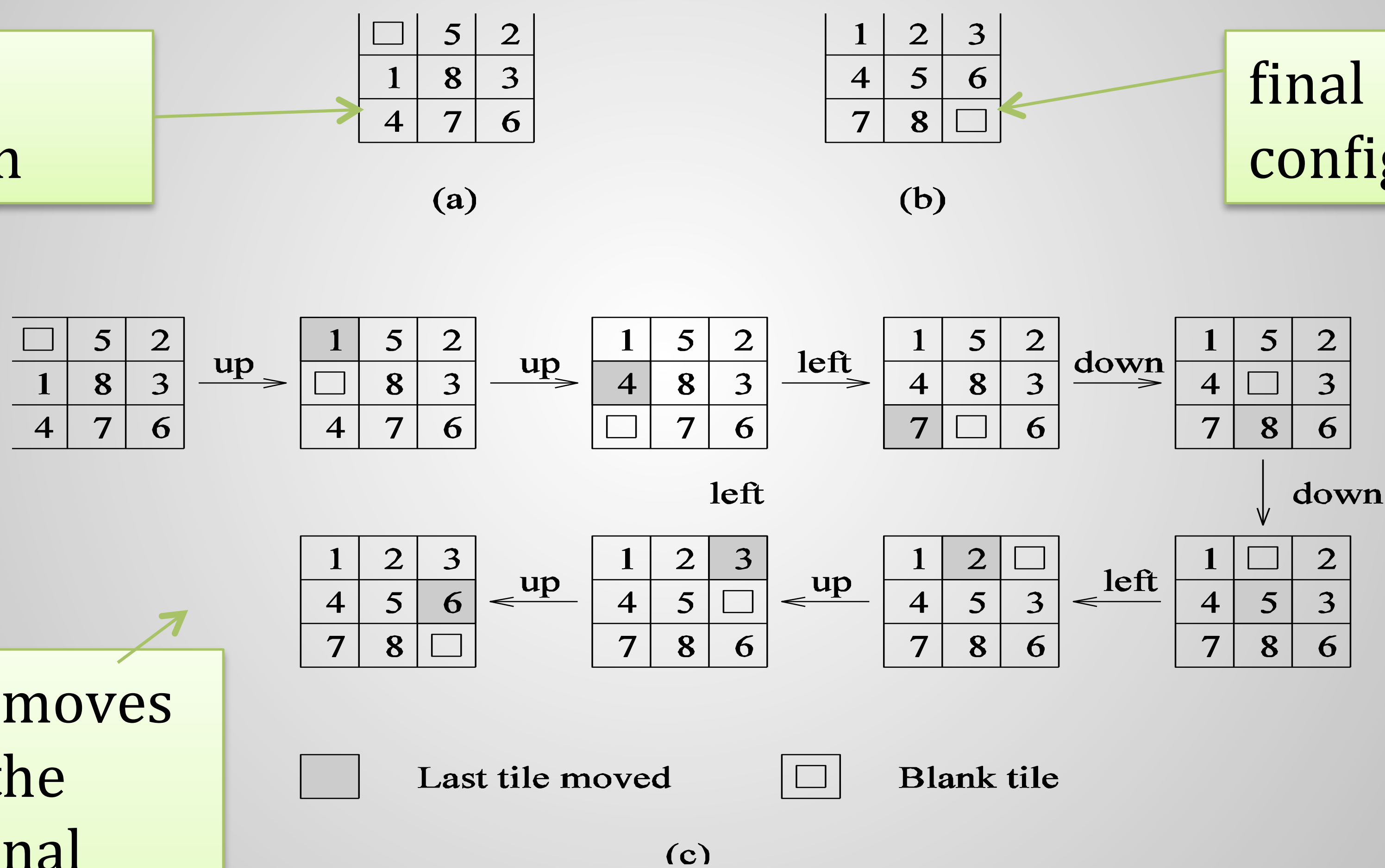
The goal is to move from a given initial position to the final position in a minimum number of moves.

□	5	2
1	8	3
4	7	6

optimization: an example

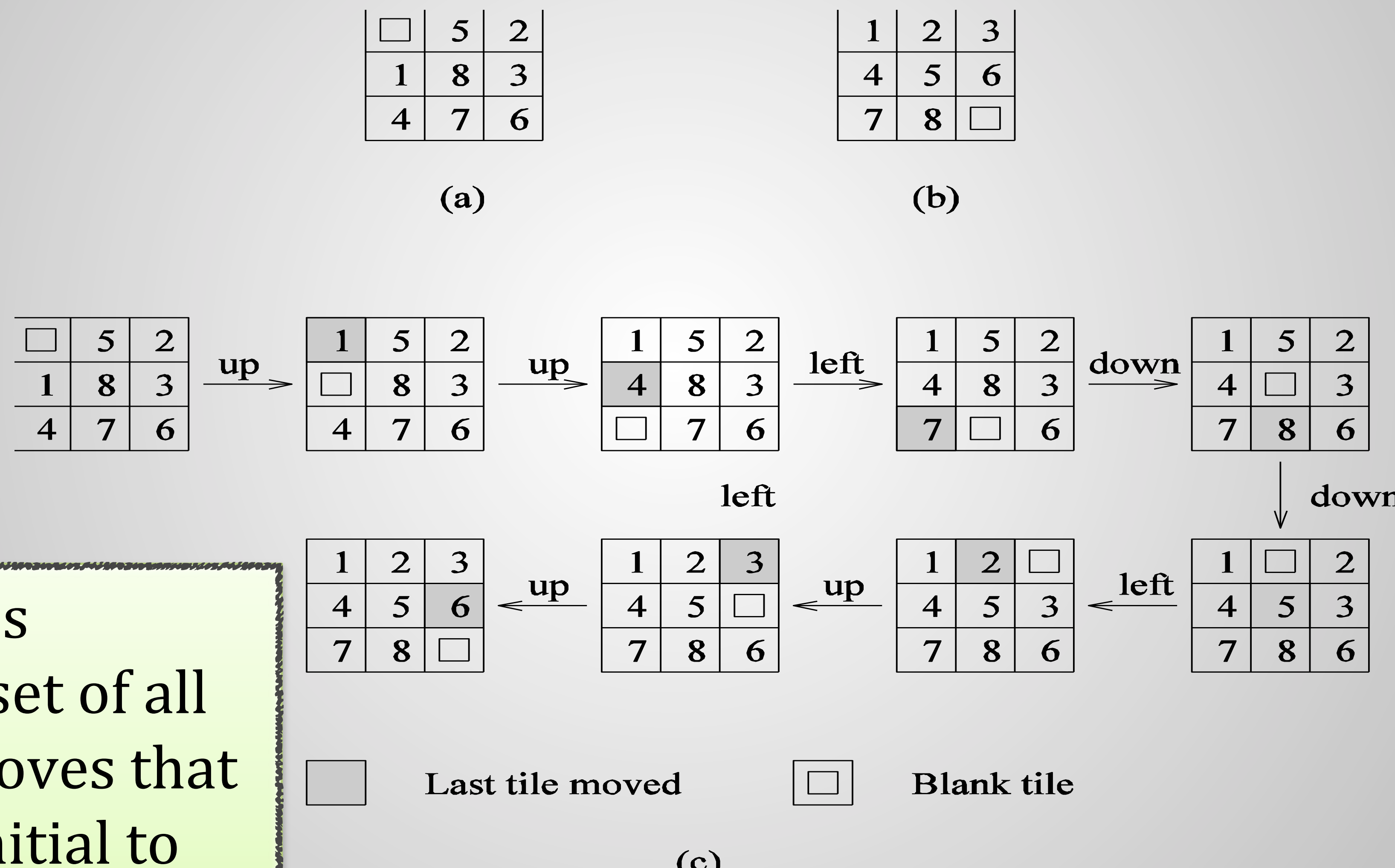
initial configuration

final configuration



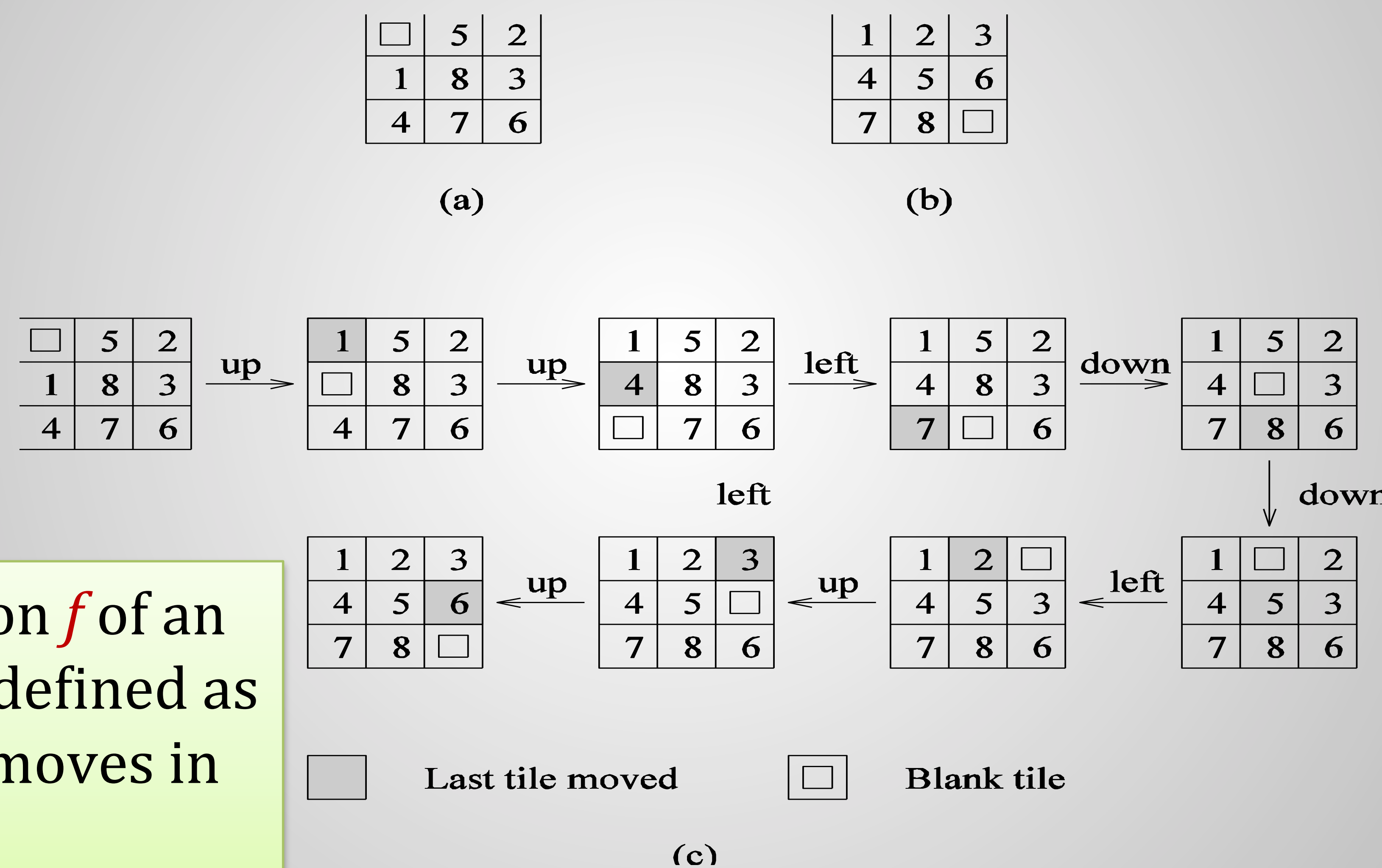
a sequence of moves leading from the initial to the final configuration.

optimization: an example

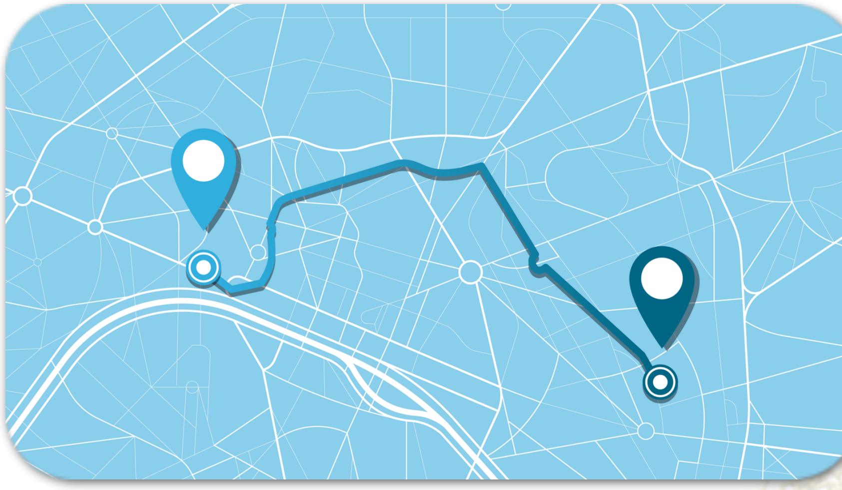


The set *S* for this problem is the set of all sequences of moves that lead from the initial to the final configurations.

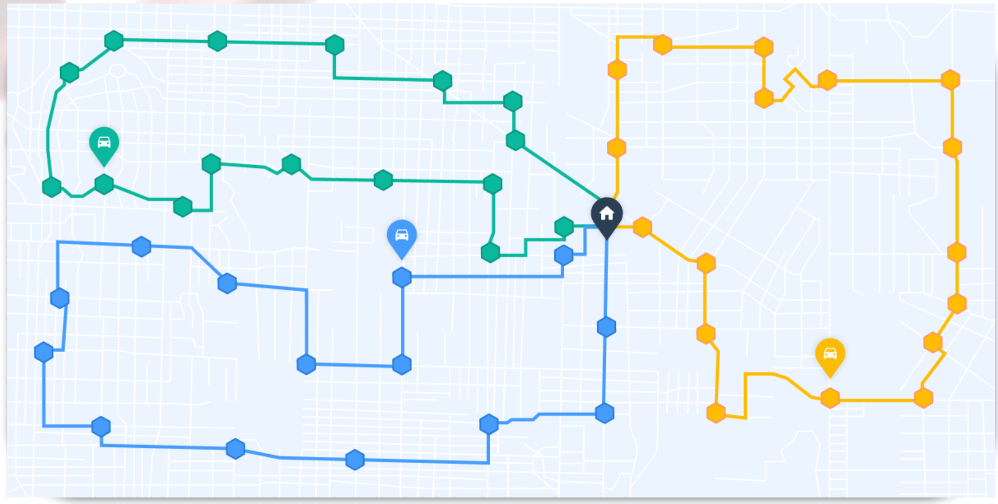
optimization: an example



The cost function f of an element in S is defined as the number of moves in the sequence.



Everything around us asks to optimize something!



Problem-Solving Methodologies

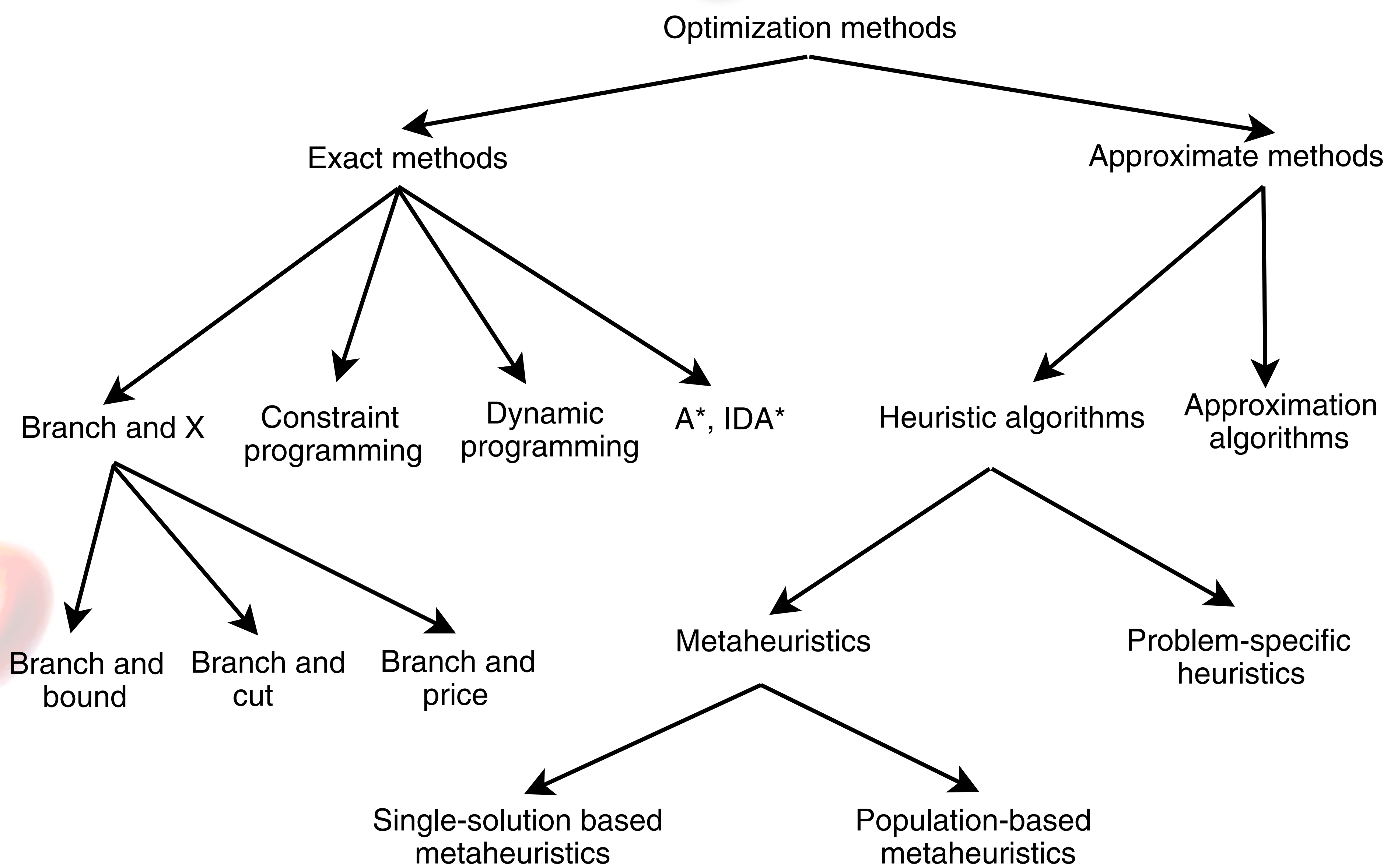
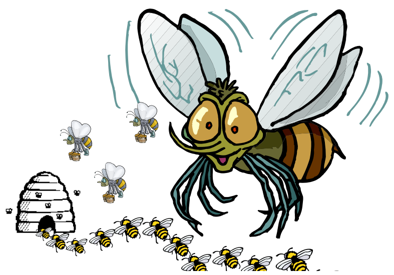


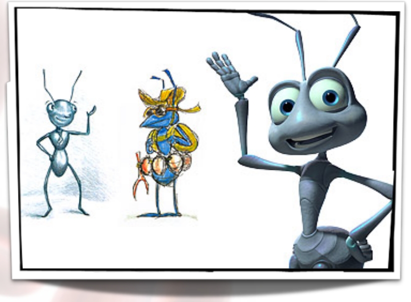
FIGURE 1.7 Classical optimization methods.

Iterative/Stochastic vs. Greedy/Deterministic

[E.G. Talbi, "Metaheuristics: from Design to Implementation", Wiley & Sons, 2009]

Deterministic versus stochastic: A deterministic metaheuristic solves an optimization problem by making deterministic decisions (e.g., local search, tabu search). In stochastic metaheuristics, some random rules are applied during the search (e.g., simulated annealing, evolutionary algorithms). In deterministic algorithms, using the same initial solution will lead to the same final solution, whereas in stochastic metaheuristics, different final solutions may be obtained from the same initial solution. This characteristic must be taken into account in the performance evaluation of metaheuristic algorithms.





Iterative versus greedy: In iterative algorithms, we start with a complete solution (or population of solutions) and transform it at each iteration using some search operators. Greedy algorithms start from an empty solution, and at each step a decision variable of the problem is assigned until a complete solution is obtained. Most of the metaheuristics are iterative algorithms.