- Heuristics
 - "to find" (from ancient Greek "ευρίσκειν")
- Meta-
 - An abstraction from another concept
 - beyond, in an upper level
 - used to complete or add to
 - E.g., meta-data = "data about data"
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 - "A heuristic around heuristics"

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- Metaheuristics...
 - ...usually incorporate mechanisms to avoid getting trapped in confined areas of the search space
 - ...usually are non-deterministic
 - ... are not problem specific (but their subordinate heuristics are)
 - ...may use some form of memory to better guide the search

- Some popular frameworks
 - Genetic Algorithms
 - Simulated Annealing
 - Tabu Search
 - Scatter Search
 - Ant Colony Optimization
 - Particle Swarm Optimization
 - Iterated Local Search
 - Variable Neighborhood Search
 - Adaptive Memory Programming

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- Metaheuristics...
 - ... can address both discrete- and continuous-domain optimization problems
 - ... are strategies that "guide" the search process
 - ...range from simple local search procedures to complex adaptive learning processes

- Metaheuristics...
 - ...efficiently explore the search space in order to find good (near-optimal) feasible solutions
 - ...provide no guarantee of global or local optimality
 - ... are agnostic to the unexplored feasible space (i.e., no "bound" information)
 - ...lack a metric of "goodness" of solution (often stop due to an external time or iteration limit)
 - ...are not based on some algebraic model *unlike exact methods!*
 - ... are often used in conjunction with an exact method



- Metaheuristics...
 - ... is a relatively new field (started in the '80s or so)
 - becomes possible because we can now afford vast amounts of computation
 - inspired from "AI," rather than "pure math"
 - lack of theoretical "rigor" (no proofs, theorems, etc. for people to pursue)



Metaheuristics classification

Trajectory-based (S-metaheuristics)



FIGURE 2.1 Main principles of single-based metaheuristics.

Population-based (P-metaheuristics)



FIGURE 3.1 Main principles of P-metaheuristics.

Algorithm 2.1	High-level template of S-metaheuristics.
Inj	put: Initial solution s ₀ .
<i>t</i> =	: 0;
Re	peat
	/* Generate candidate solutions (partial or complete neighborhood) from st */
(Generate $(C(s_t))$;
	/* Select a solution from $C(s)$ to replace the current solution s_t^*
1	$s_{t+1} = \text{Select}(C(s_t));$
1	t = t + 1;
Un	til Stopping criteria satisfied
Ou	tput: Best solution found.

Algorithm 3.1 High-level template of P-metaheuristics.

 $P = P_0; /* \text{ Generation of the initial population } */$ t = 0; **Repeat** Generate(P'_t); /* Generation a new population */ $P_{t+1} = \text{Select-Population}(P_t \cup P'_t); /* \text{ Select new population } */$ t = t + 1;Until Stopping criteria satisfied **Output:** Best solution(s) found.





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Input: Initial solution s_0 . t = 0; Repeat /* Generate candidate solutions (partial or complete neighborhood) from s_t */ Generate($C(s_t)$); /* Select a solution from C(s) to replace the current solution s_t */ $s_{t+1} = \text{Select}(C(s_t))$; t = t + 1; Until Stopping criteria satisfied Output: Best solution found.



Stop because of no improvement in region $C(s_2)$



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Input: Initial solution s₀.
t = 0;
Repeat
 /* Generate candidate solutions (partial or complete neighborhood) from s_t */
 Generate(C(s_t));
 /* Select a solution from C(s) to replace the current solution s_t */
 s_{t+1} = Select(C(s_t));
 t = t + 1;
Until Stopping criteria satisfied
Output: Best solution found.



Turns out two global optima in this problem, but none was identified

- One was missed during search of region C(s₁)
- One was far away from searched space





Repeat

```
Generate(P'_t); /* Generation a new population */

P_{t+1} = Select-Population(P_t \cup P'_t); /* Select new population */

t = t + 1;

Until Stopping criteria satisfied

Output: Best solution(s) found.
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```
2<sup>nd</sup> population
```

-()))



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Again, optimum may or may not have been sampled

• Typically, the incumbent always remains in the population, so need only focus on last generation



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