Algorithmes Évolutionnaires (M2 MIAGE IA²)

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Séance 1
Introduction

Objectifs de cet enseignement

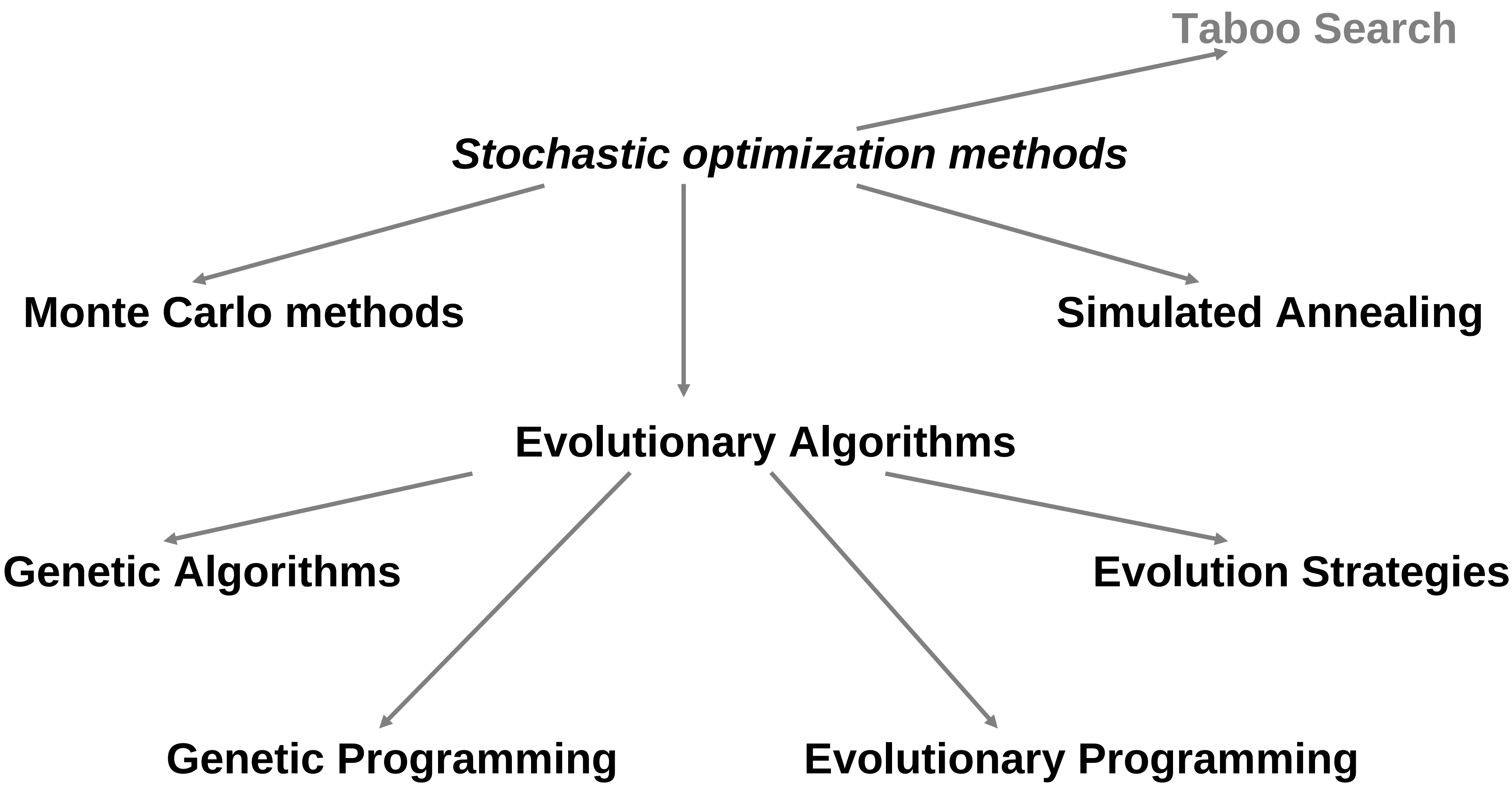
- Fournir une compréhension claire de la métaphore et des concepts sur lesquels repose le calcul évolutionniste
- Fournir une compréhension de certaines des techniques évolutives qui sont devenues des composants essentiels de la boîte à outils de résolution de problèmes du « *soft computing* ».
- Après avoir suivi ce cours, vous saurez
  - ce que l'on entend par algorithme évolutionnaire (AE)
  - comment et pourquoi les AE fonctionnent
  - ce que sont les algorithmes génétiques, la programmation évolutionnaire, les stratégies évolutionnaires et la programmation génétique
  - comment ces techniques peuvent être appliqués à la résolution de problèmes pratiques.

Organisation

- Page Web (transparents, énoncés, etc.)

  http://www.i3s.unice.fr/~tettaman/Classes/AE/
- Modalités de contrôle des connaissances
  - TP ramassés à chaque séance
  - Contrôle terminal écrit (à confirmer)

Taxonomy


Taboo Search
Stochastic optimization methods
Monte Carlo methods
Simulated Annealing
Evolutionary Algorithms
Genetic Algorithms
Evolution Strategies
Genetic Programming
Evolutionary Programming

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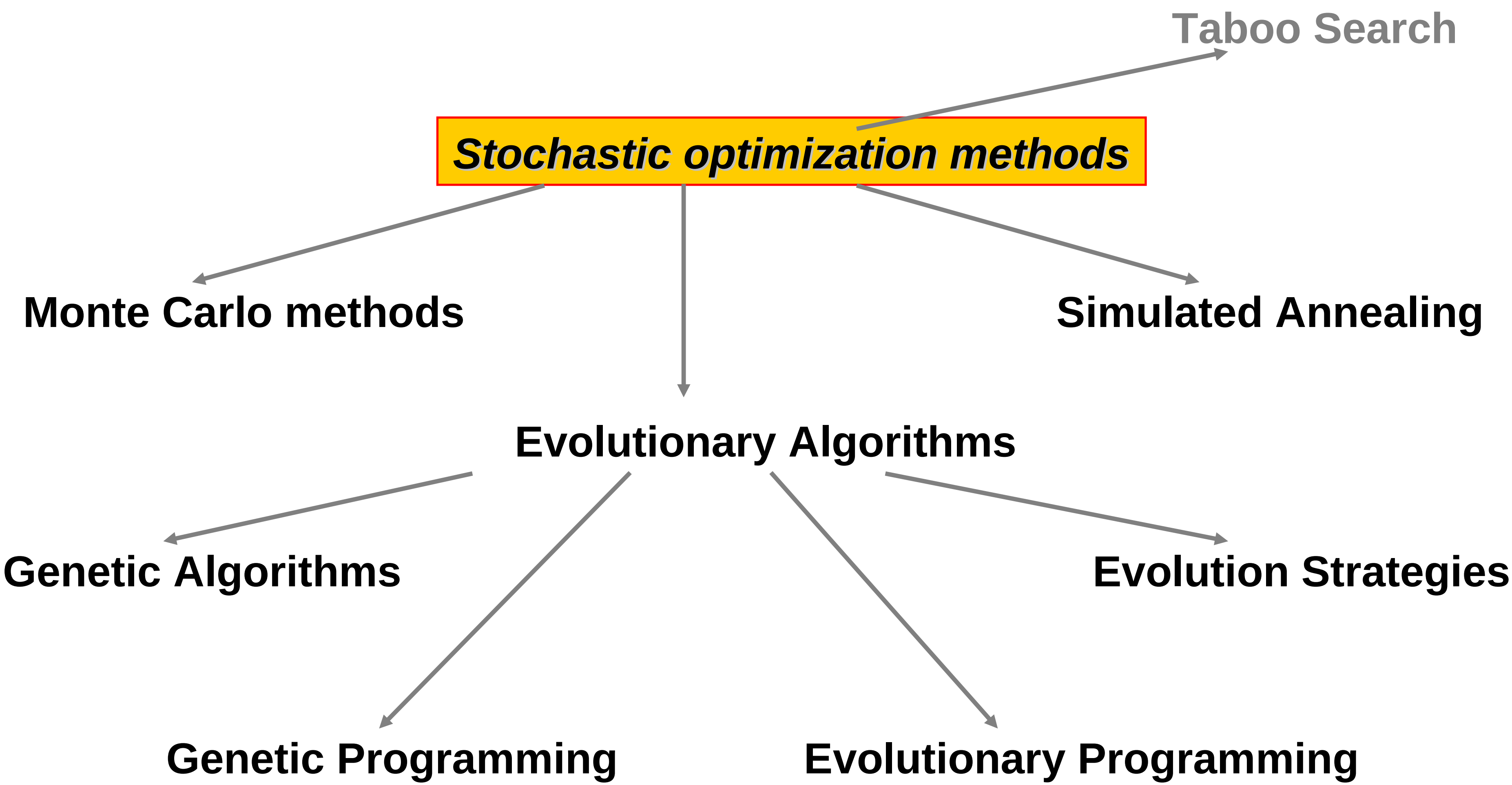
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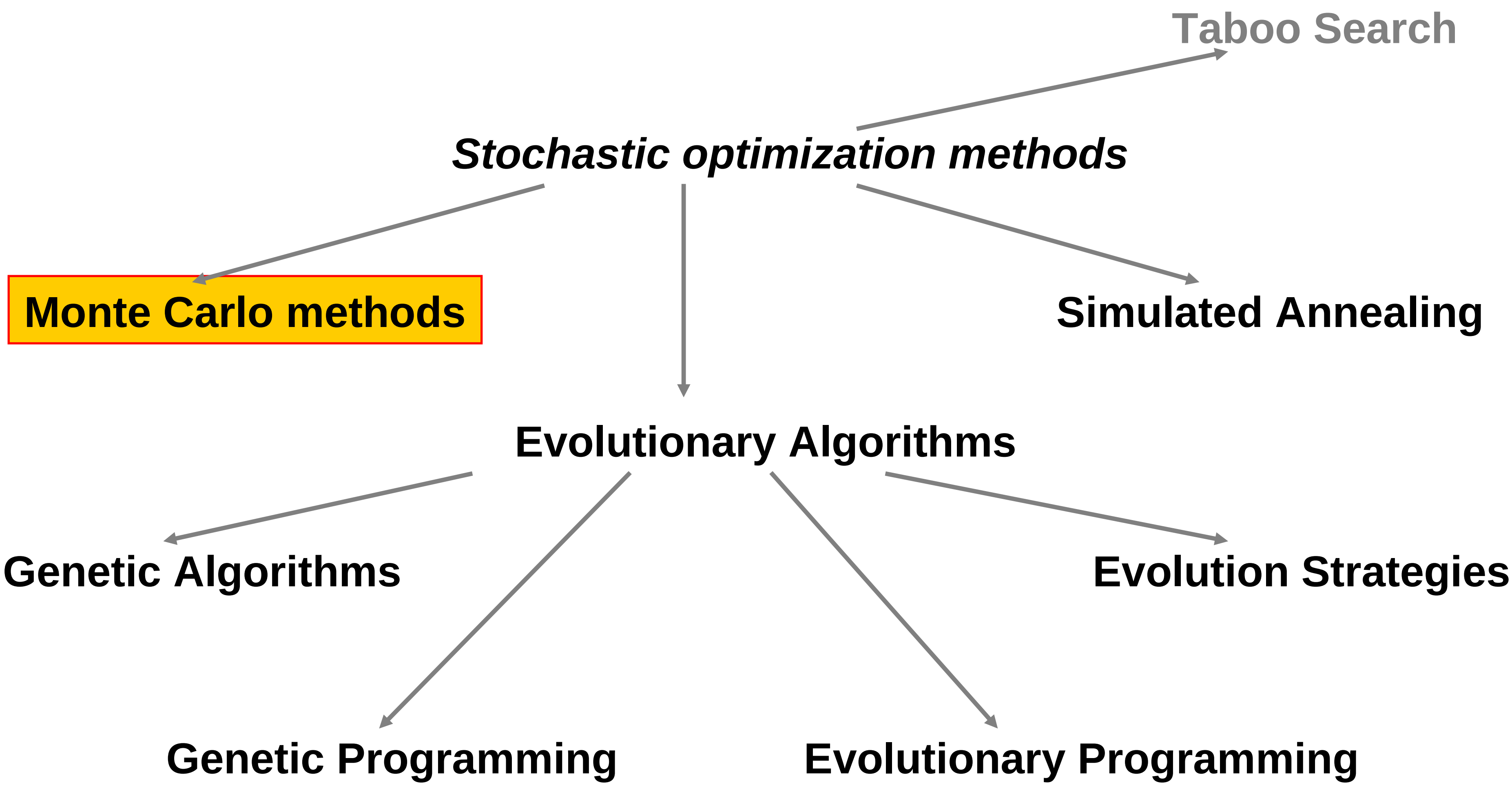
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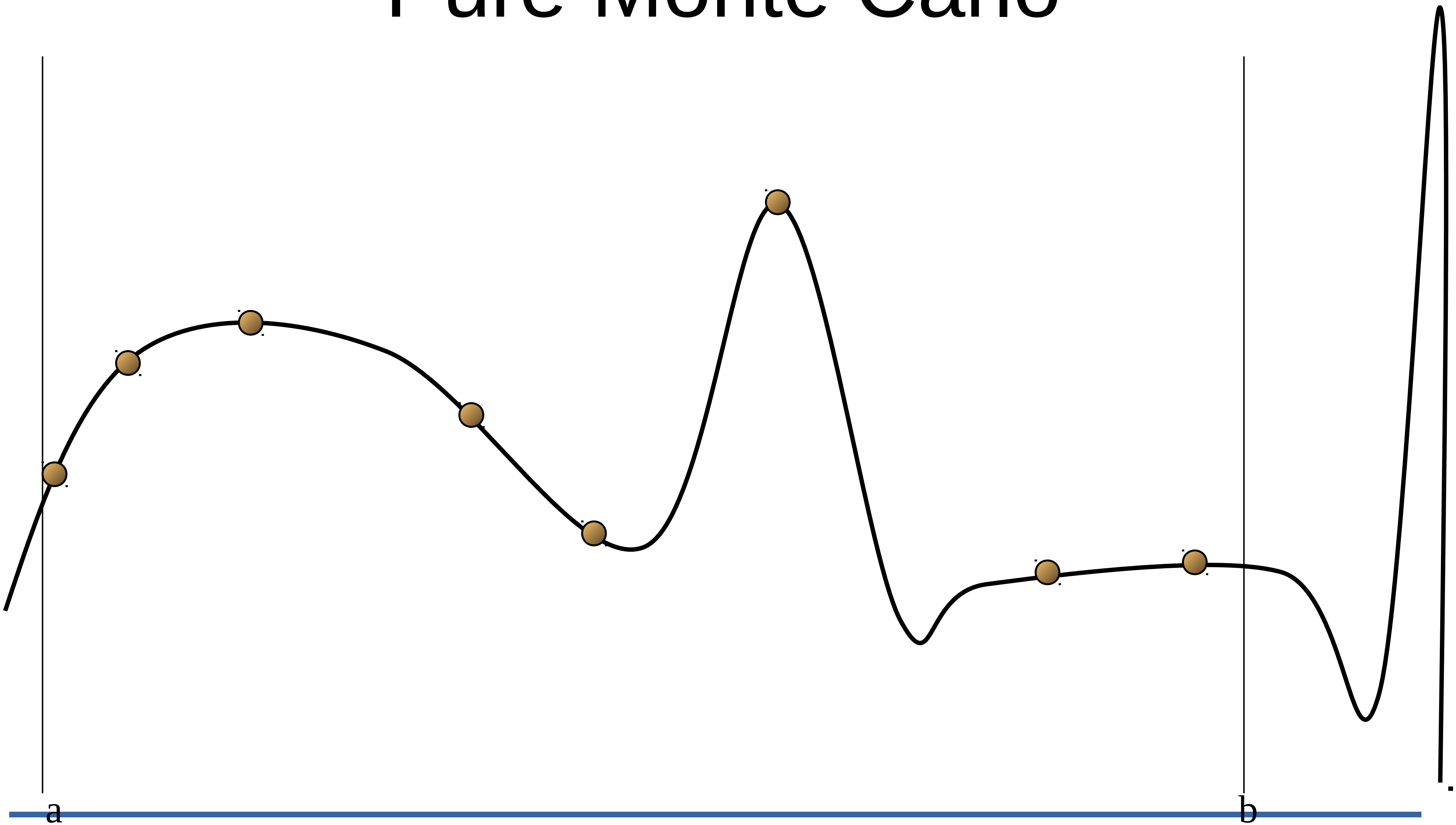
Pure Monte Carlo

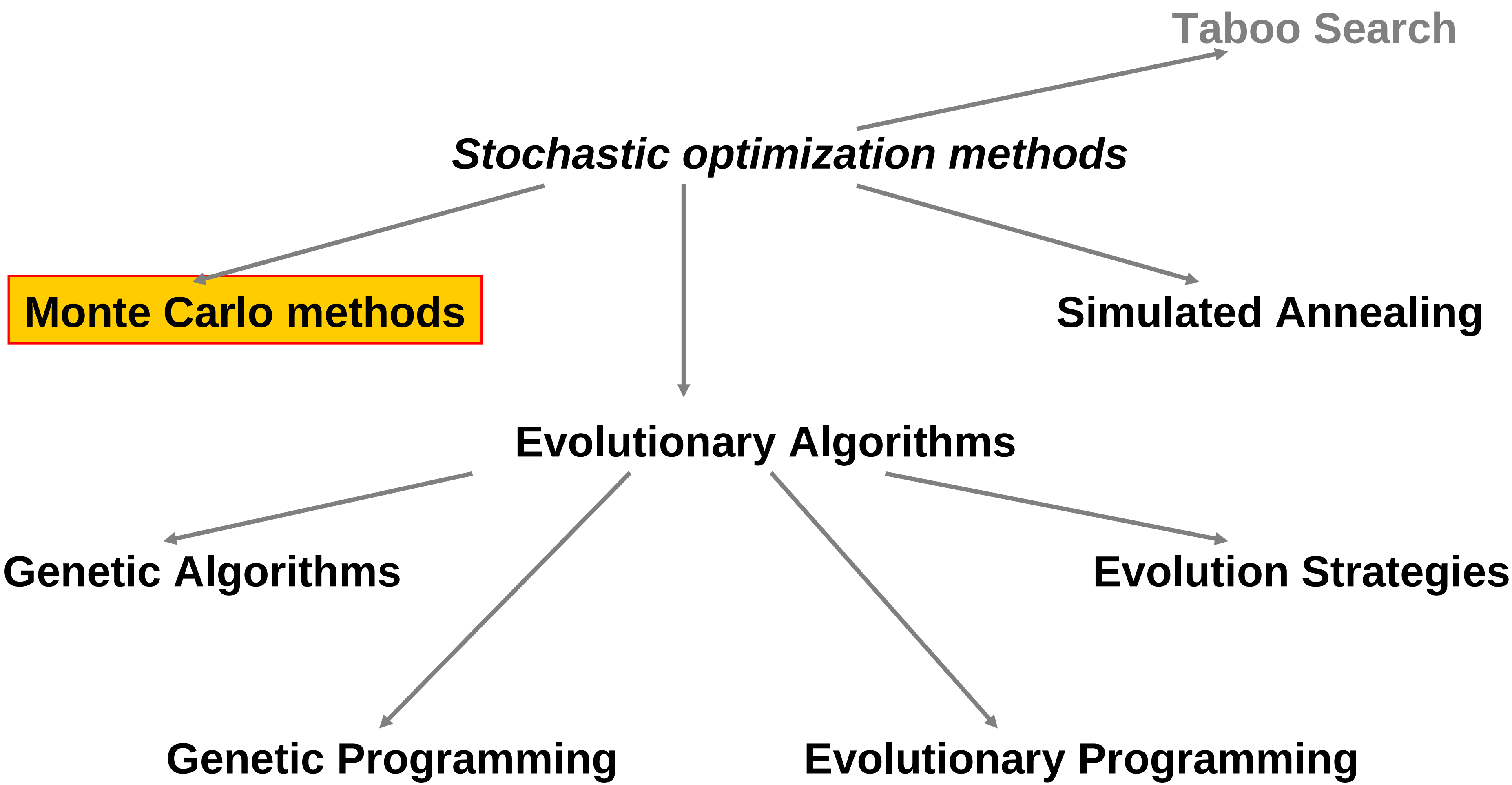


Convergence in probability

$$\lim_{t \to \infty} \Pr\left[\left| f(x_t) - f(x^*) \right| < \varepsilon\right] = 1$$

$$\lim_{t \to \infty} f(x_t) = f(x^*)$$ **"almost surely"**

Taxonomy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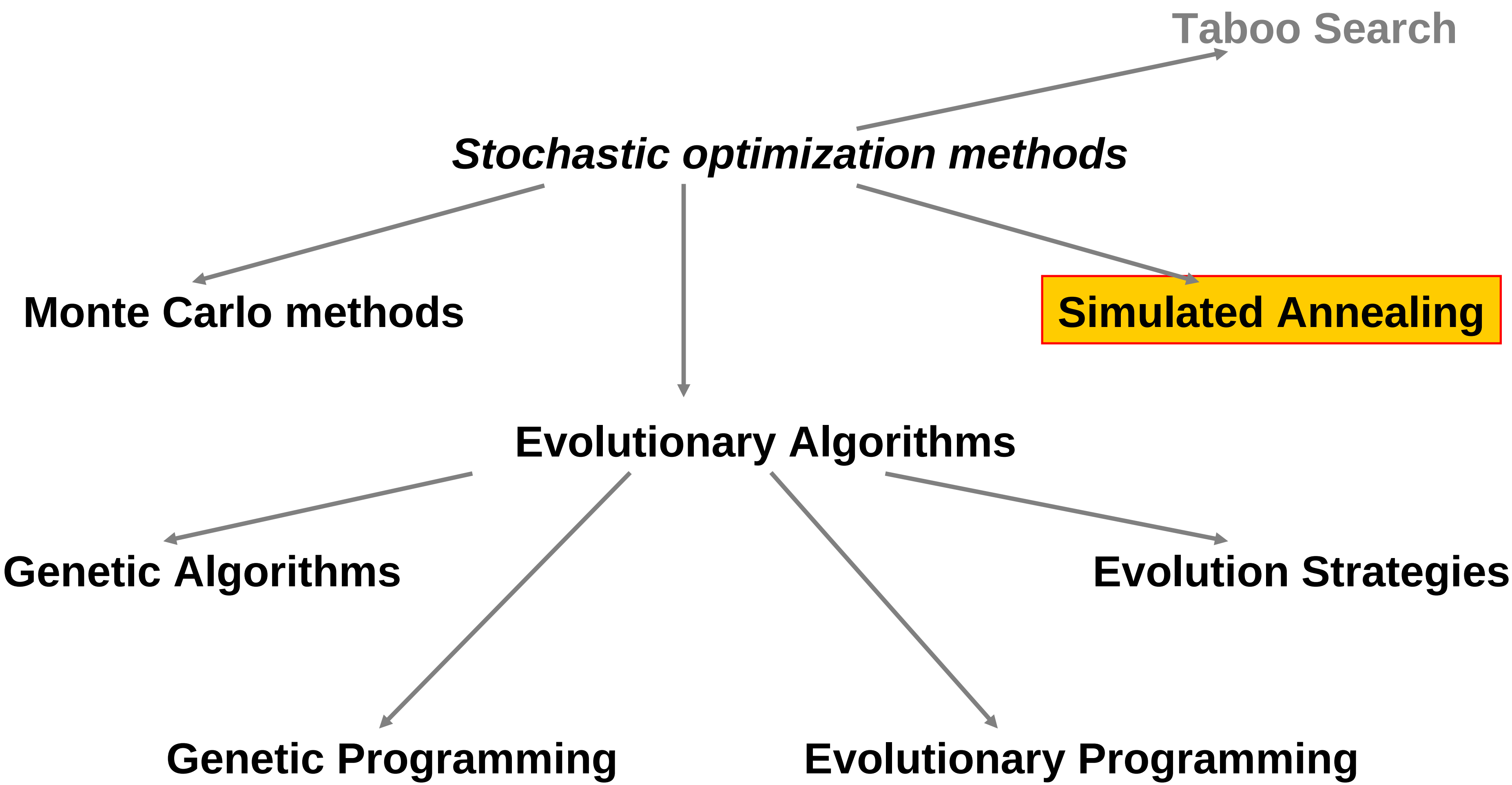
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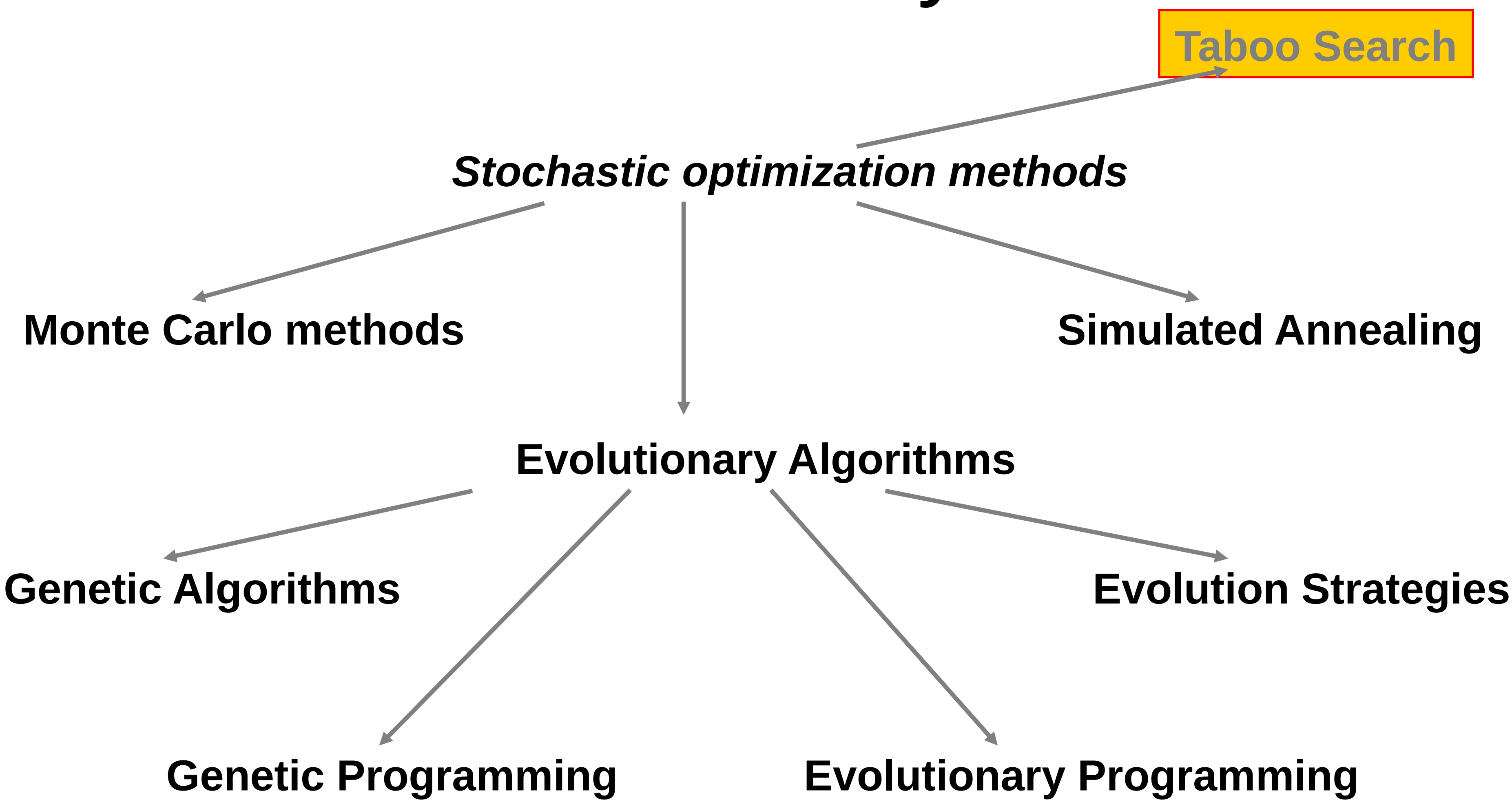
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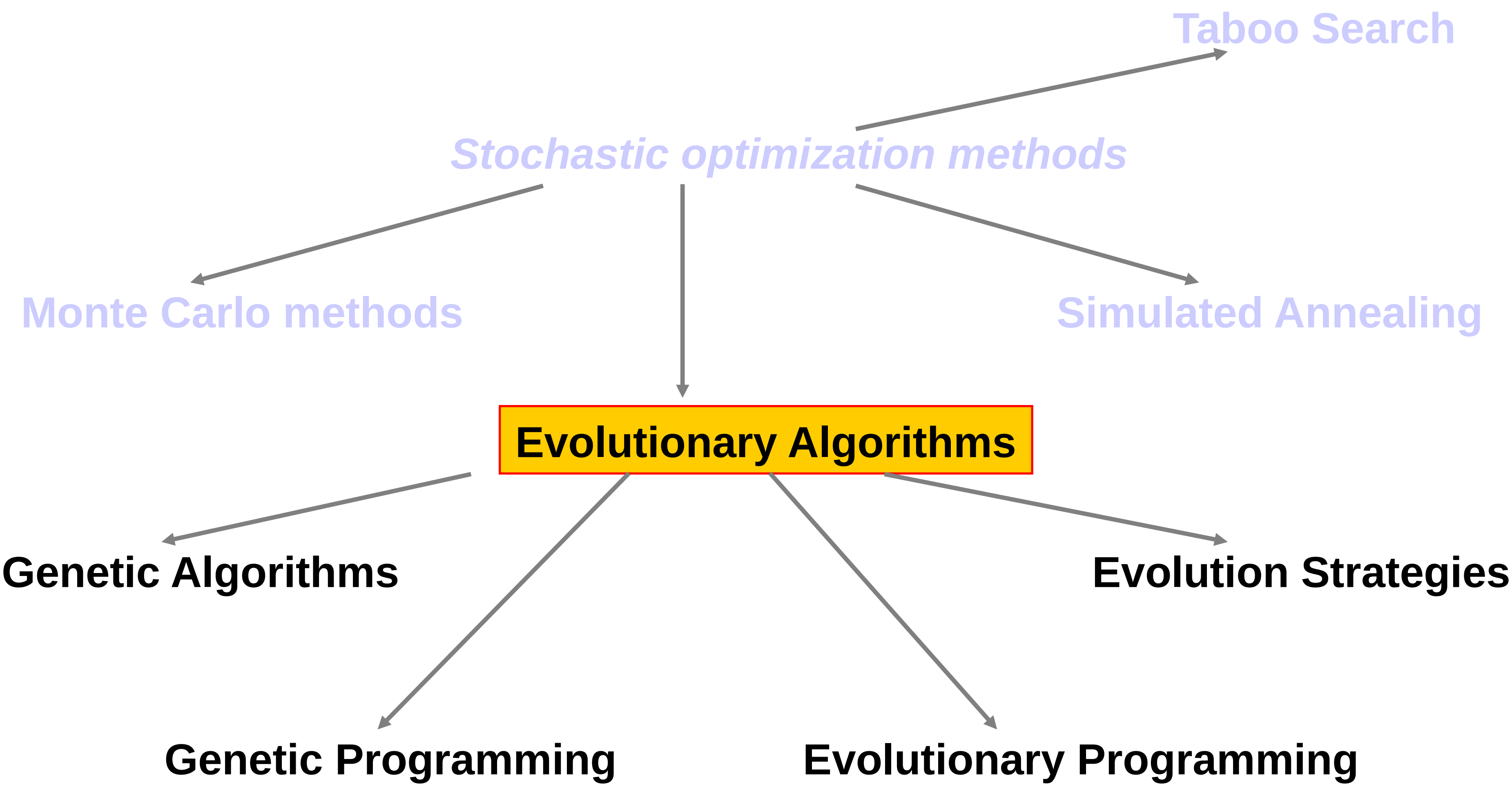

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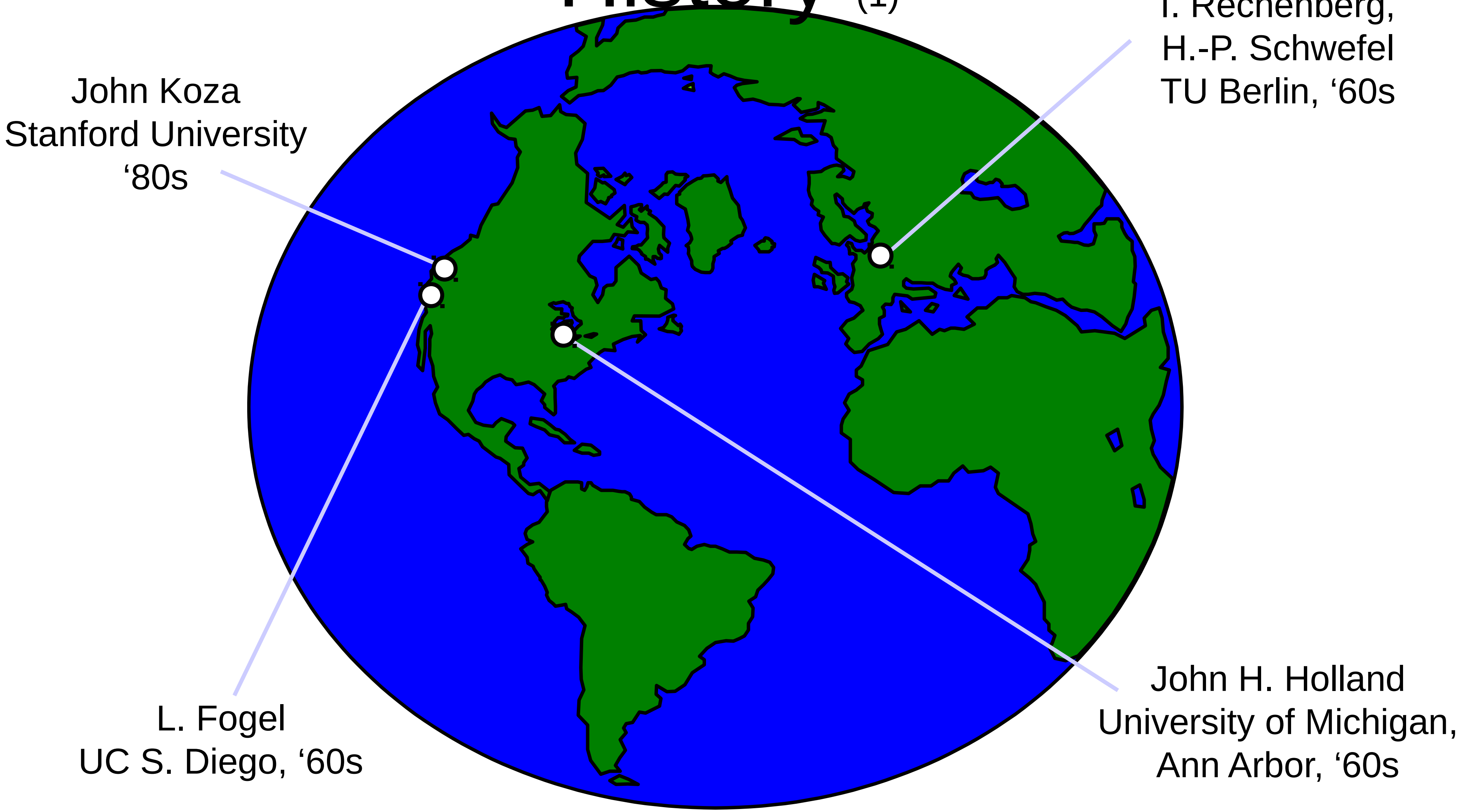
Distinctive Features of EAs

- operate on appropriate encoding of solutions;
- population search;
- no regularity conditions requested;
- probabilistic transitions.

History (1)



John Koza
Stanford University
'80s
I. Rechenberg,
H.-P. Schwefel
TU Berlin, '60s
L. Fogel
UC S. Diego, '60s
John H. Holland
University of Michigan,
Ann Arbor, '60s

History (2)

1859 Charles Darwin: inheritance, variation, natural selection

1957 G. E. P. Box: random mutation & selection for optimization

1958 Fraser, Bremermann: computer simulation of evolution

1964 Rechenberg, Schwefel: mutation & selection

1966 Fogel et al.: evolving automata - "evolutionary programming"

History (3)

1975 Holland: crossover, mutation & selection - “reproductive plan”

1975 De Jong: parameter optimization - “genetic algorithm”

1989 Goldberg: first textbook

1991 Davis: first handbook

1992 Michalewicz: Genetic Algorithms + Data Structures = Evolution Programs

History (4)

- 1993 Koza: evolving LISP programs - “genetic programming”
- 1998 Ryan & O’Neill: Grammatical Evolution
- 1999 Storn & Price: Differential Evolution
- 2001 Poli: schema theorem for GP
- 2002 Stanley & Miikkulainen: NEAT

The Metaphor

EVOLUTION	PROBLEM SOLVING
Environment	Object problem
Individual	Candidate solution
Fitness	Quality

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Alternative Views of Evolutionary Algorithms

- Operations Research: optimization method
- Decision Theory: optimal decision
- Machine Learning: learning technique
- Artificial Life: artificial counterpart of natural evolution
- Biology: tool for testing evolutionary models

Optimization Problem

Cost function $c : S \to \mathbf{R}$

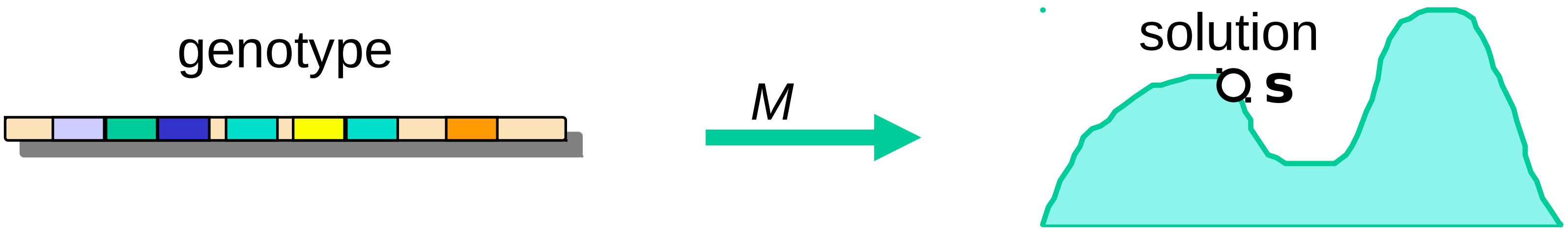
minimize $c(\mathbf{s})$

subject to $\mathbf{s} \in S_{FEAS}.$

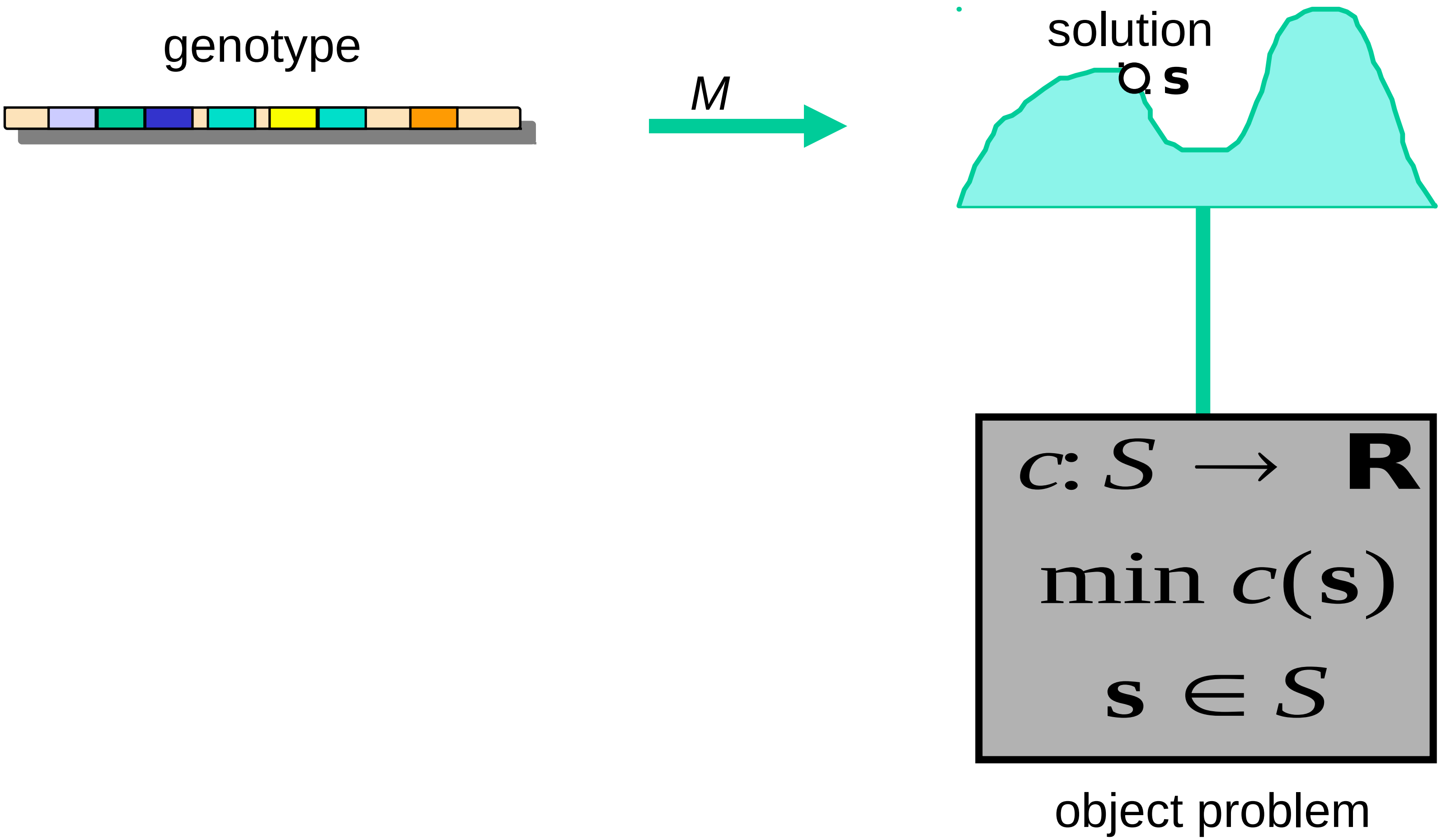
Object problem and Fitness

genotype

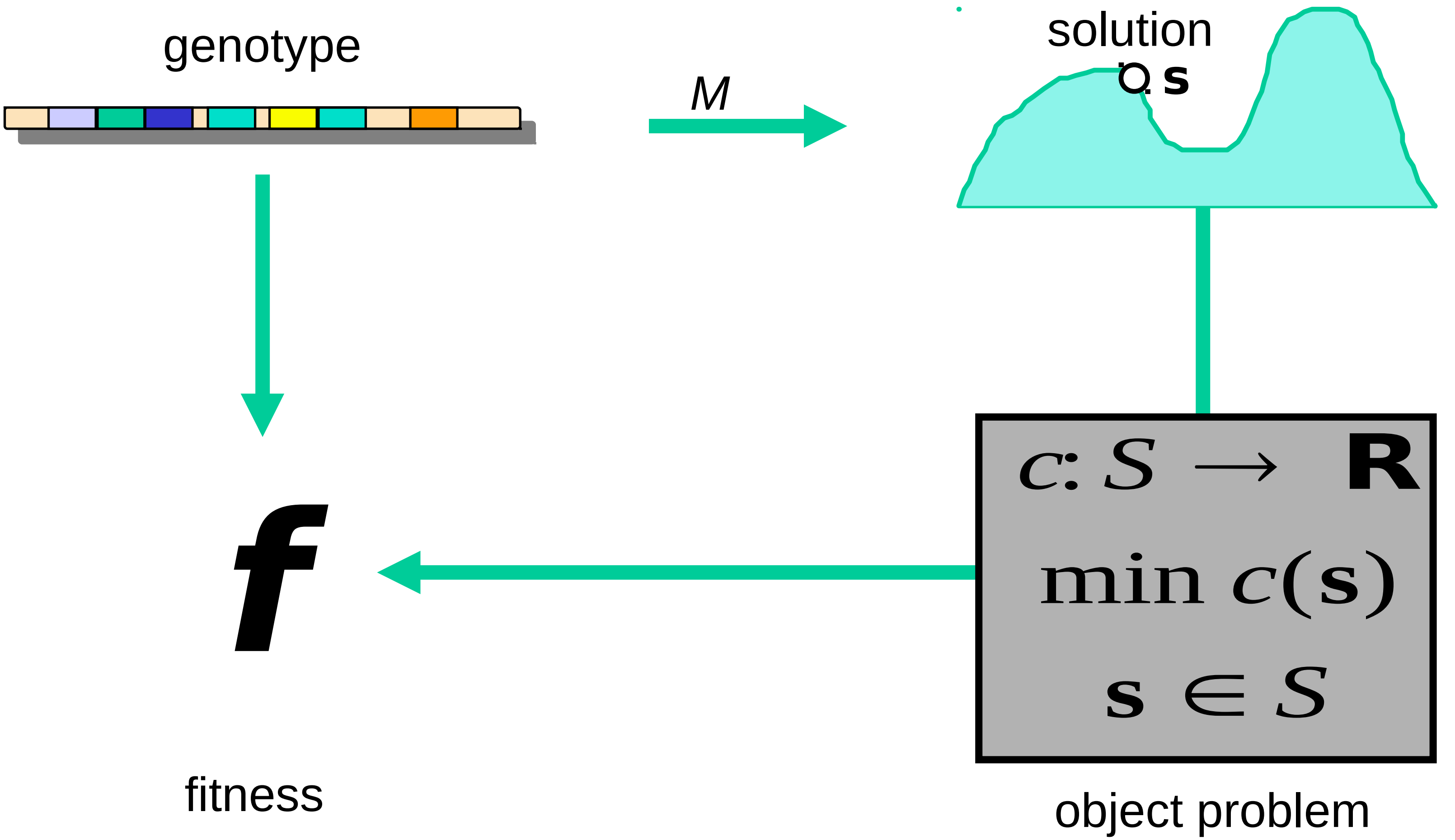
Object problem and Fitness



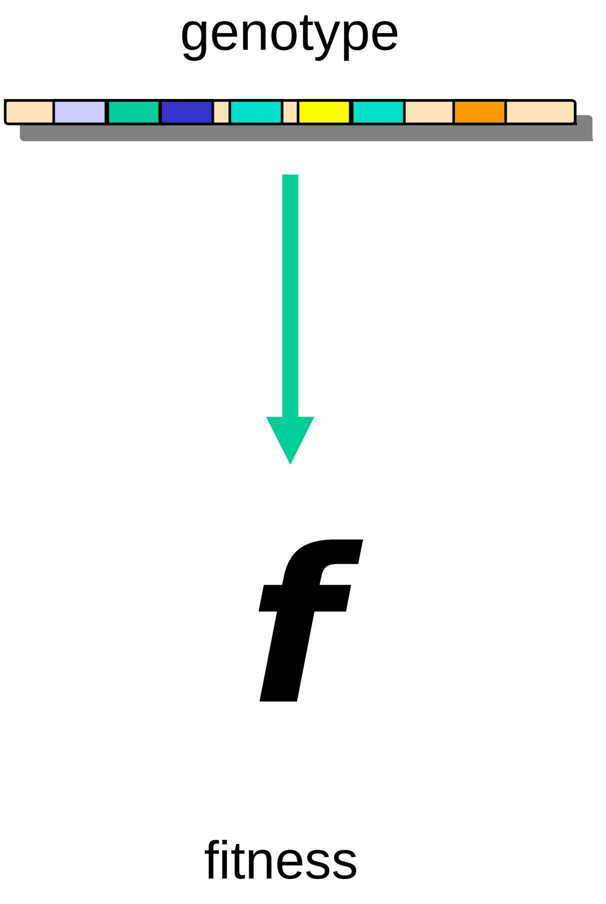
Object problem and Fitness



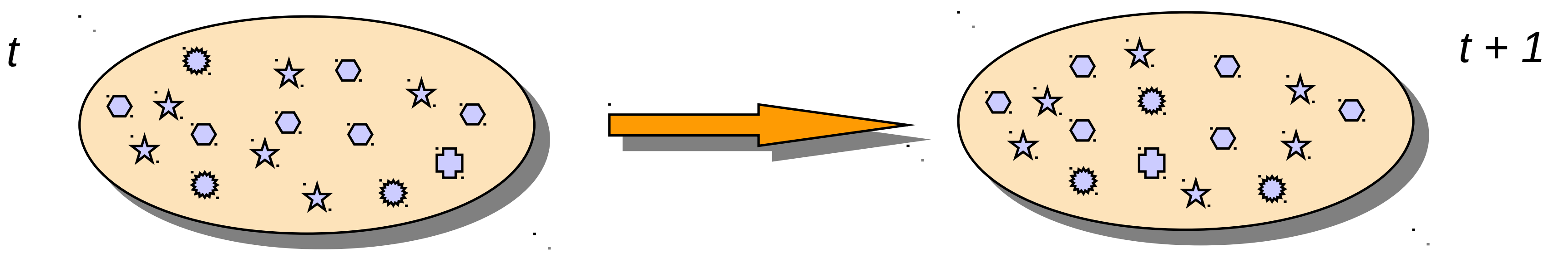
Object problem and Fitness



Object problem and Fitness



The Ingredients



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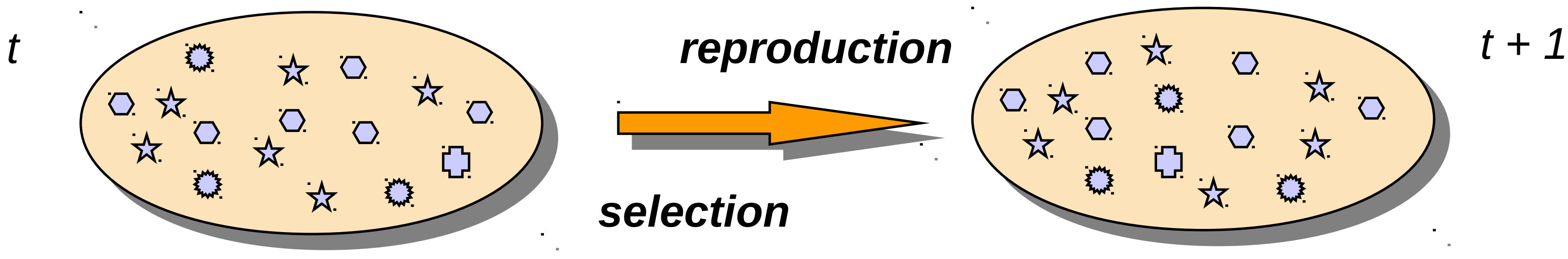

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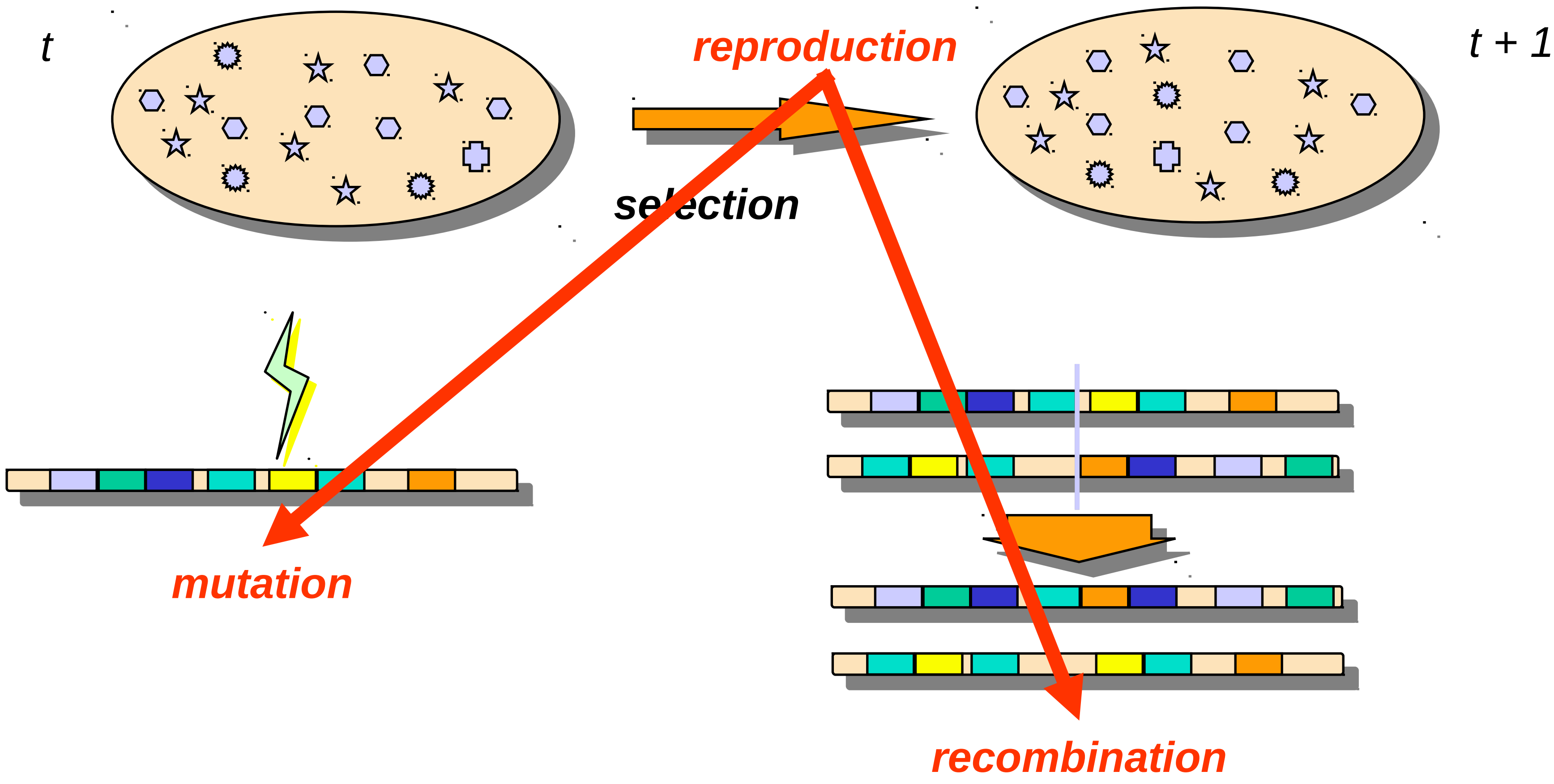

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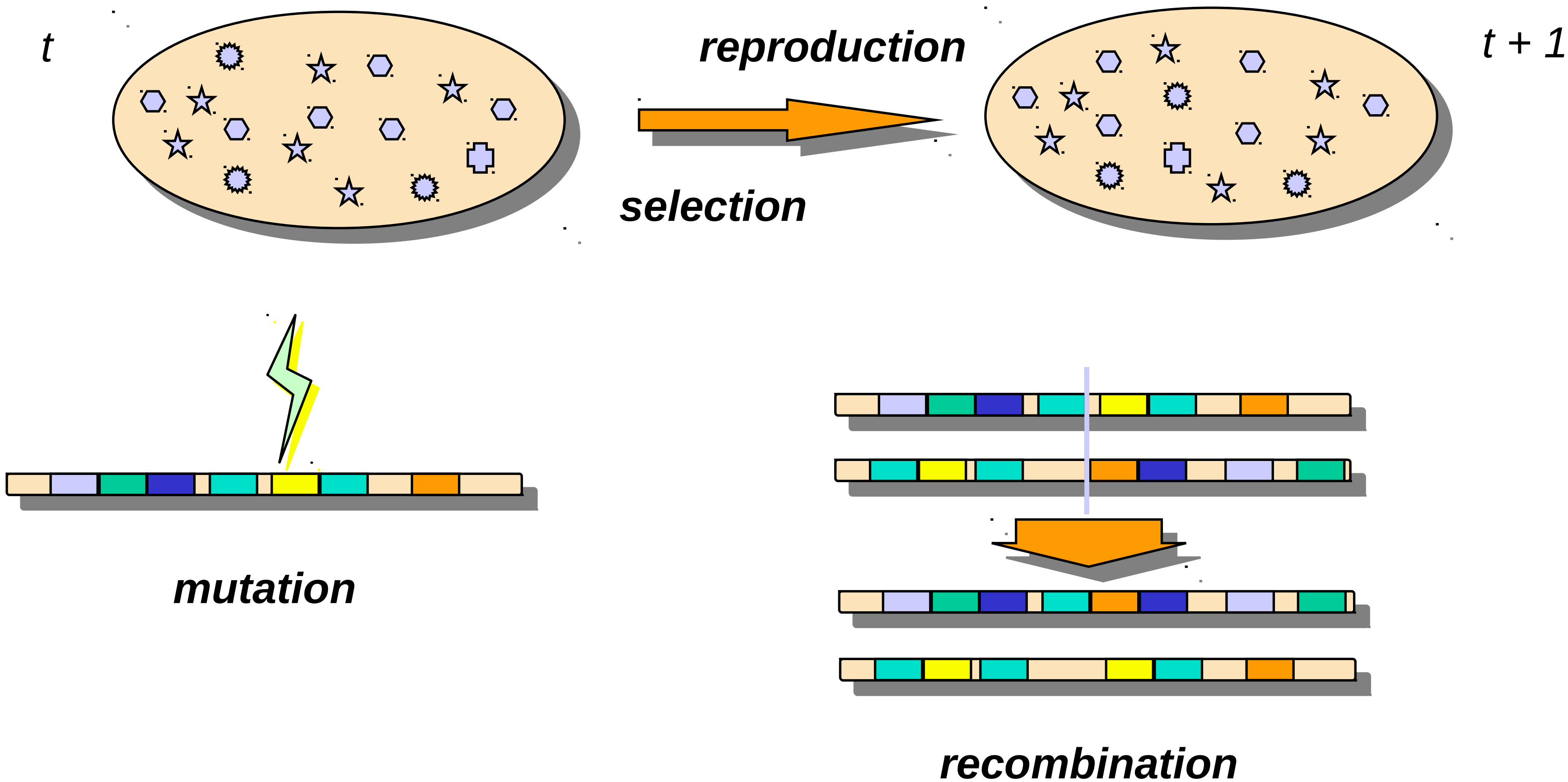
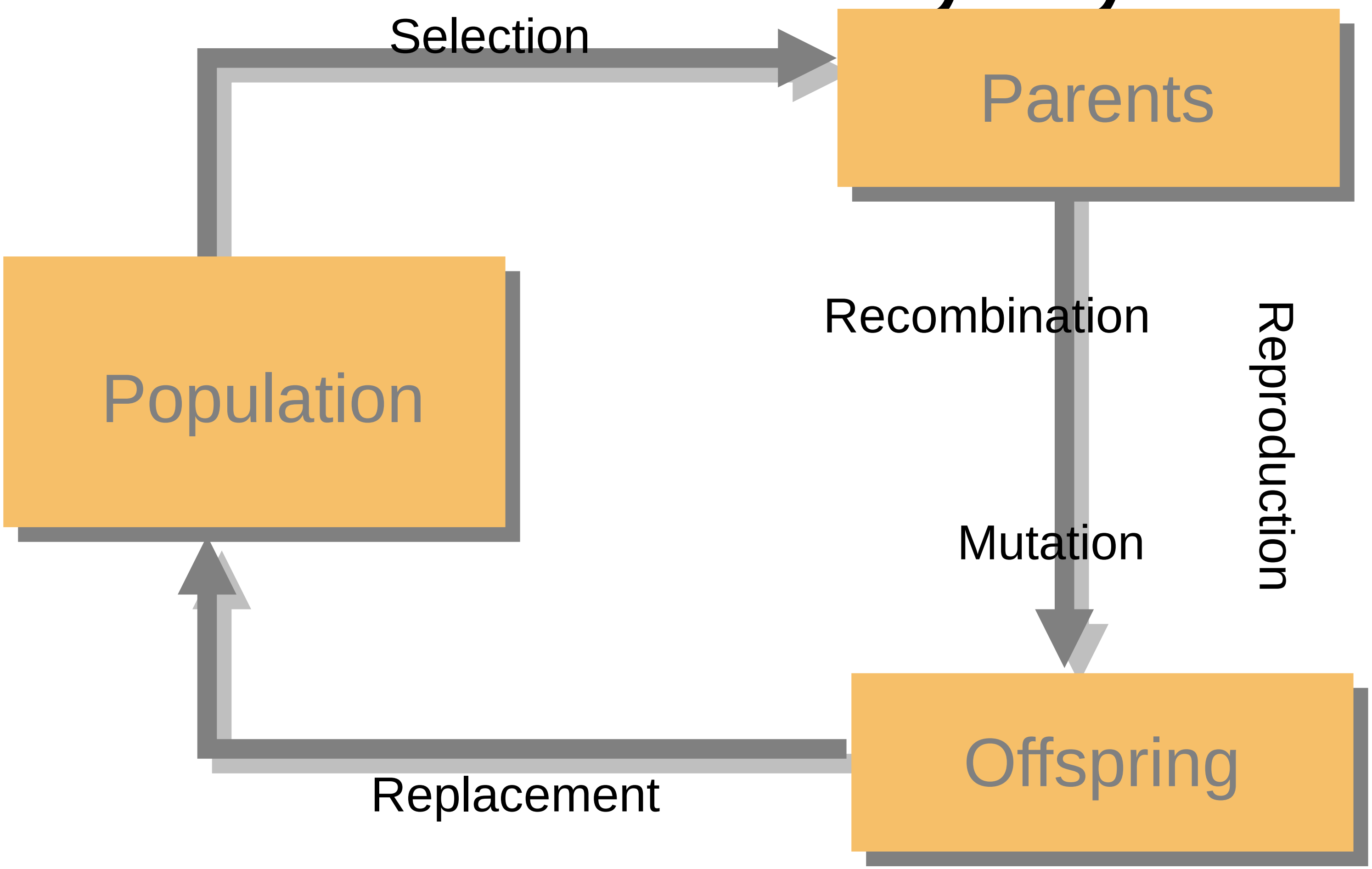


Pseudocode

```
generation = 0;
SeedPopulation(popSize); // at random or from a file
while(!TerminationCondition())
{
    generation = generation + 1;
    CalculateFitness();        // ... of new genotypes
    Selection();               // select genotypes that will reproduce
    Crossover(p_cross);        // mate p_cross of them on average
    Mutation(p_mut);           // mutate all the offspring with Bernoulli
                               // probability p_mut over genes
}
```

The Evolutionary Cycle

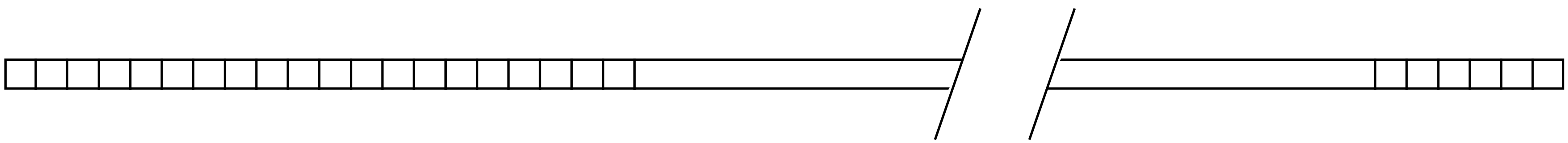


A Sample Genetic Algorithm

- The MAXONE problem
- Genotypes are bit strings
- Fitness-proportionate selection
- One-point crossover
- Flip mutation (transcription error)

The MAXONE Problem

Problem instance: a string of *l* binary cells, $\gamma \in \{0, 1\}^l$:



Fitness:

$$f(\gamma) = \sum_{i=1}^{l} \gamma_i$$

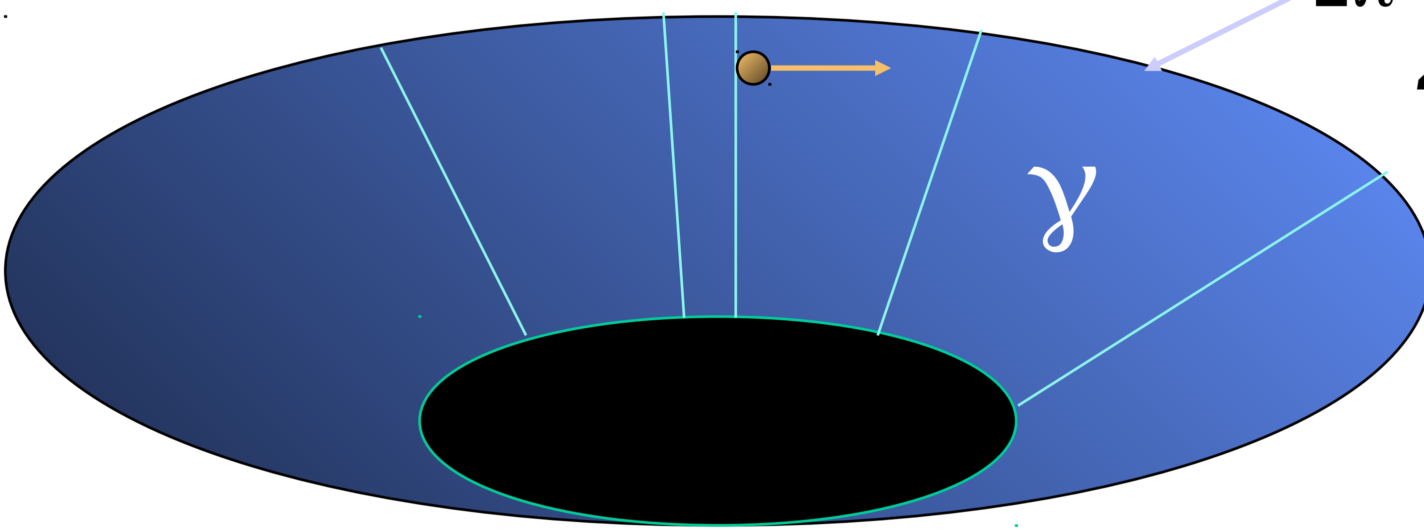
Objective: maximize the number of ones in the string.

Fitness Proportionate Selection

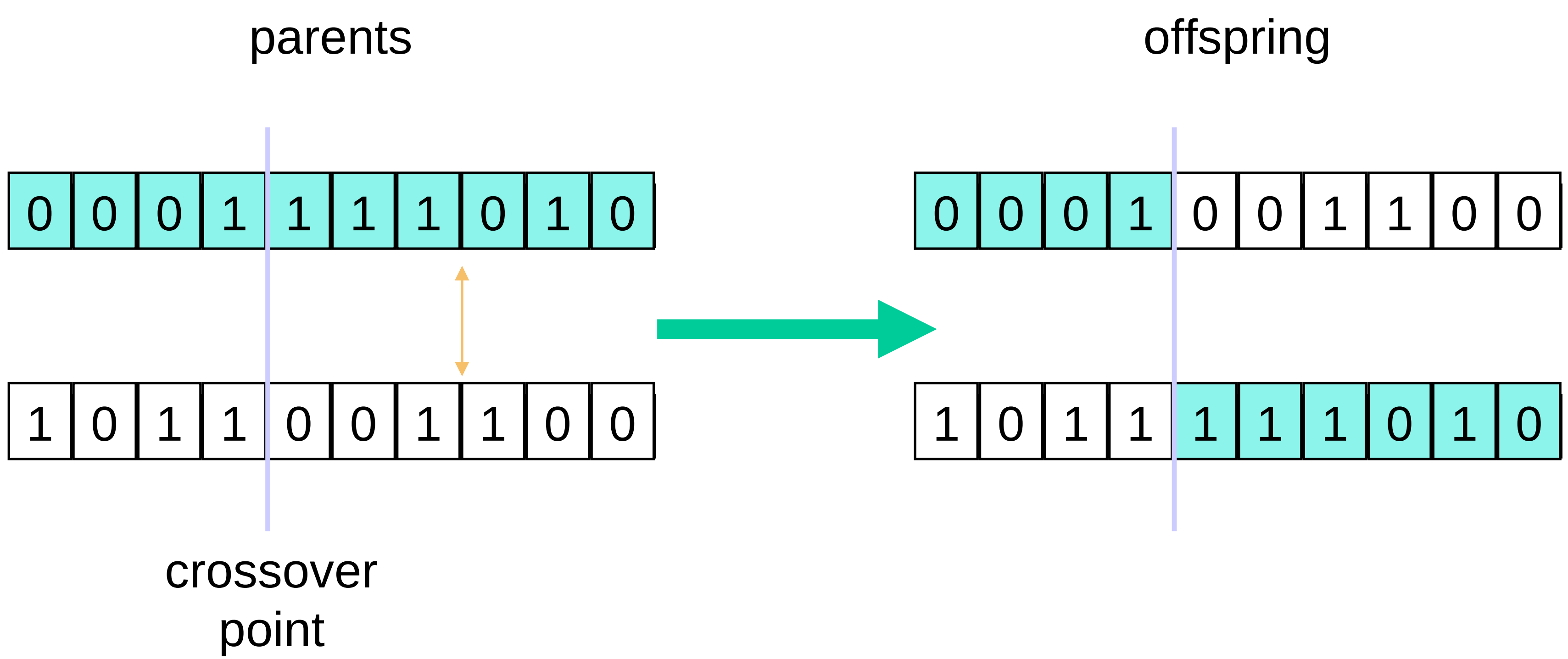
Probability of γ being selected: $$P(\gamma) = \frac{f(\gamma)}{\sum f}$$

Implementation: “Roulette Wheel”

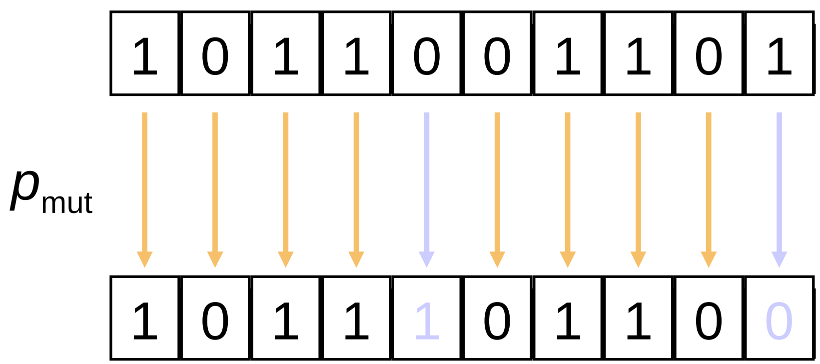
$$2\pi \frac{f(\gamma)}{\sum f}$$



One-Point Crossover



Mutation



independent Bernoulli transcription errors

Example: Selection

0111011011	f = 7	Cf = 7	P = 0.125
1011011101	f = 7	Cf = 14	P = 0.125
1101100010	f = 5	Cf = 19	P = 0.089
0100101100	f = 4	Cf = 23	P = 0.071
1100110011	f = 6	Cf = 29	P = 0.107
1111001000	f = 5	Cf = 34	P = 0.089
0110001010	f = 4	Cf = 38	P = 0.071
1101011011	f = 7	Cf = 45	P = 0.125
0110110000	f = 4	Cf = 49	P = 0.071
0011111101	f = 7	Cf = 56	P = 0.125

Random sequence: 43, 1, 19, 35, 15, 22, 24, 38, 44, 2

Example: Recombination & Mutation

0111011011	→	0111011011	→	0111111011	f = 8
0111011011	→	0111011011	→	0111011011	f = 7
110 | 1100010	→	1100101100	→	1100101100	f = 5
010 | 0101100	→	0101100010	→	0101100010	f = 4
1 | 100110011	→	1100110011	→	1100110011	f = 6
1 | 100110011	→	1100110011	→	1000110011	f = 5
0110001010	→	0110001010	→	0110001010	f = 4
1101011011	→	1101011011	→	1101011011	f = 7
011000 | 1010	→	0110001011	→	0110001011	f = 5
110101 | 1011	→	1101011010	→	1101011010	f = 6

Example: Replacement

0111011011	f = 7	0111111011	f = 8
1011011101	f = 7	0111011011	f = 7
1101100010	f = 5	1100101100	f = 5
0100101100	f = 4	0101100010	f = 4
1100110011	f = 6	1100110011	f = 6
1111001000	f = 5	1000110011	f = 5
0110001010	f = 4	0110001010	f = 4
1101011011	f = 7	1101011011	f = 7
0110110000	f = 4	0110001011	f = 5
0011111101	f = 7	1101011010	f = 6
TOTAL = 56		TOTAL = 57