COMP 5660/6660 - Evolutionary Computing - Lecture Slides

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Computational Problem Solving

- Step 1: build abstract/computational model of the real-world

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- "Everything Should Be Made as Simple as Possible, But Not Simpler"[1]
- Step 3: map solution back to real-world

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- A **hyper-heuristic** is a meta-heuristic for a space of programs

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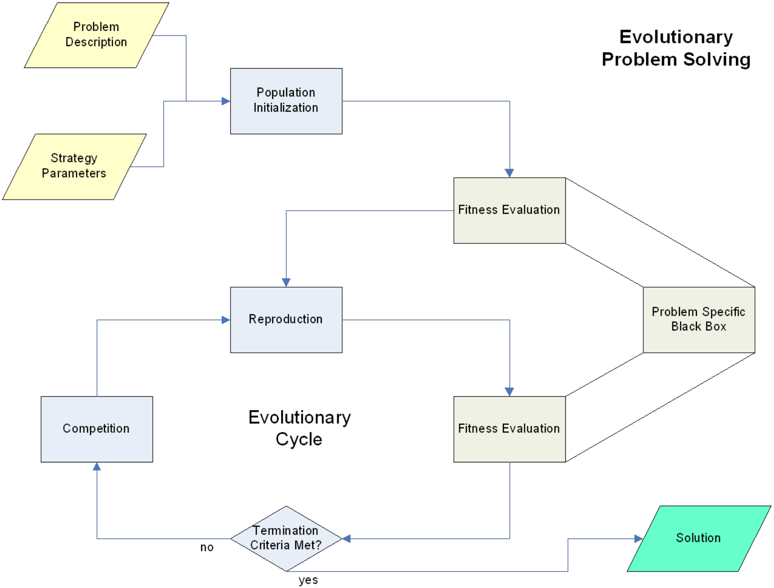
Evolutionary Cycle



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- If F is not surjective and $x^* \notin F(G)$, then the EA cannot find the global optimum. Therefore one should think twice before choosing a non-surjective decoder function if one cannot guarantee that the global optimum is still reachable.
- F does not need to be injective, but realize there is less to search if F is injective so there should be sufficient compensation, such as limiting F(G) to valid solutions in a constraint satisfaction problem.

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2. Modify $fitness(p)$ to exclude items that would exceed C_{max}