Grand Challenges in Evolutionary Computing: Part I

Dr. Daniel Tauritz

Director, Natural Computation Laboratory

Associate Professor, Department of Computer Science

Research Investigator, Intelligent Systems Center

Investigator, Energy Research & Development Center

Why we need Evolutionary Computing

- Modern society faces very complex problems
- Underlying computational problems typically very hard to solve (e.g., NP-Complete)
- Associated search spaces non-linear, non-differentiable, non-continuous, non-convex
- Traditional optimization algorithms don’t work
- Evolutionary Algorithms (EAs) often do work

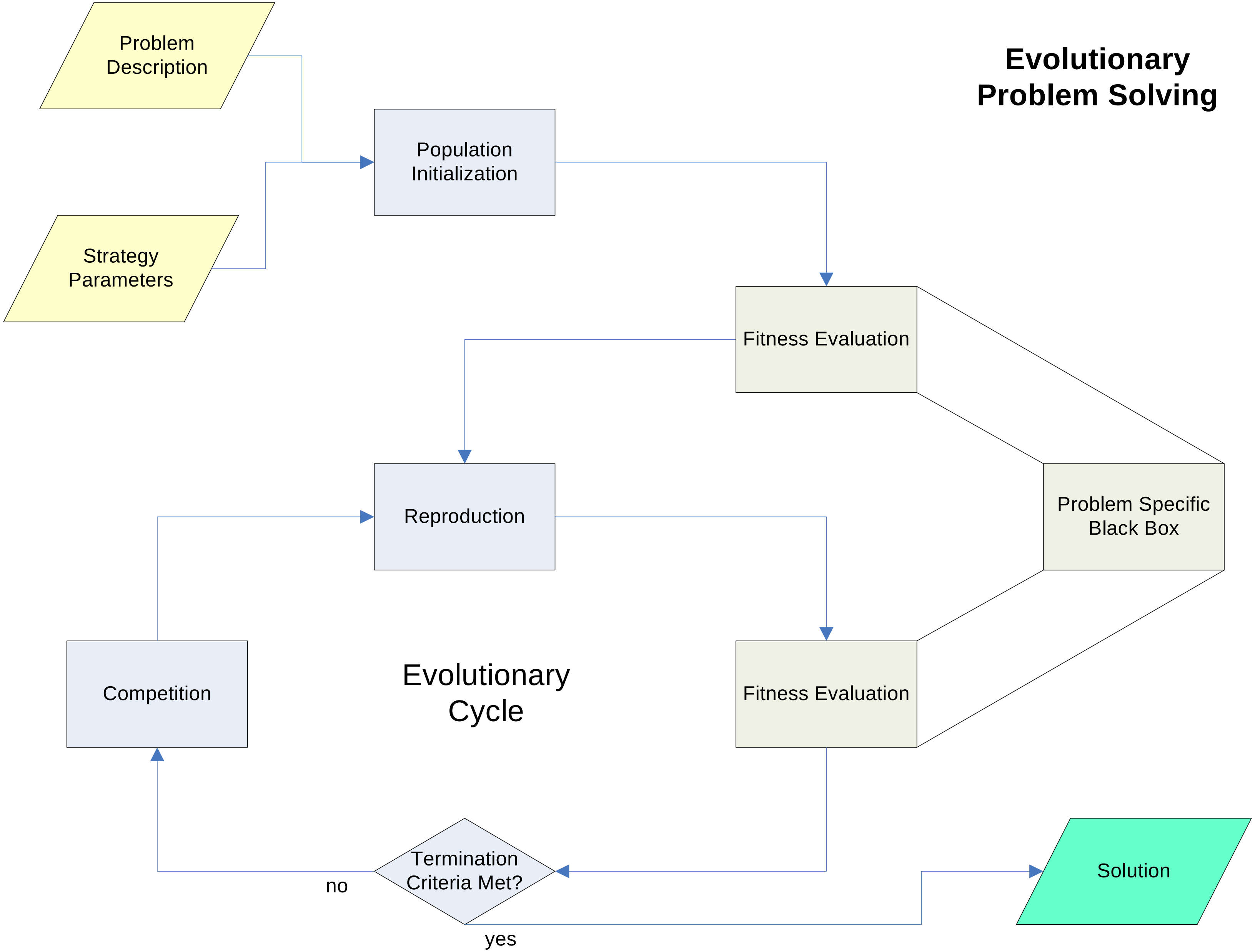
What Evolutionary Computing is

- The field of Evolutionary Computing (EC) studies the theory and application of Evolutionary Algorithms (EAs)
- EAs can be described as a class of stochastic, population-based optimization algorithms inspired by natural evolution, genetics, and population dynamics

Intuitive view of how EAs work

- Trial-and-error (aka generate-and-test)
- Graduated solution quality creates virtual gradient
- Stochastic local & global search of solution landscape

Evolutionary Problem Solving



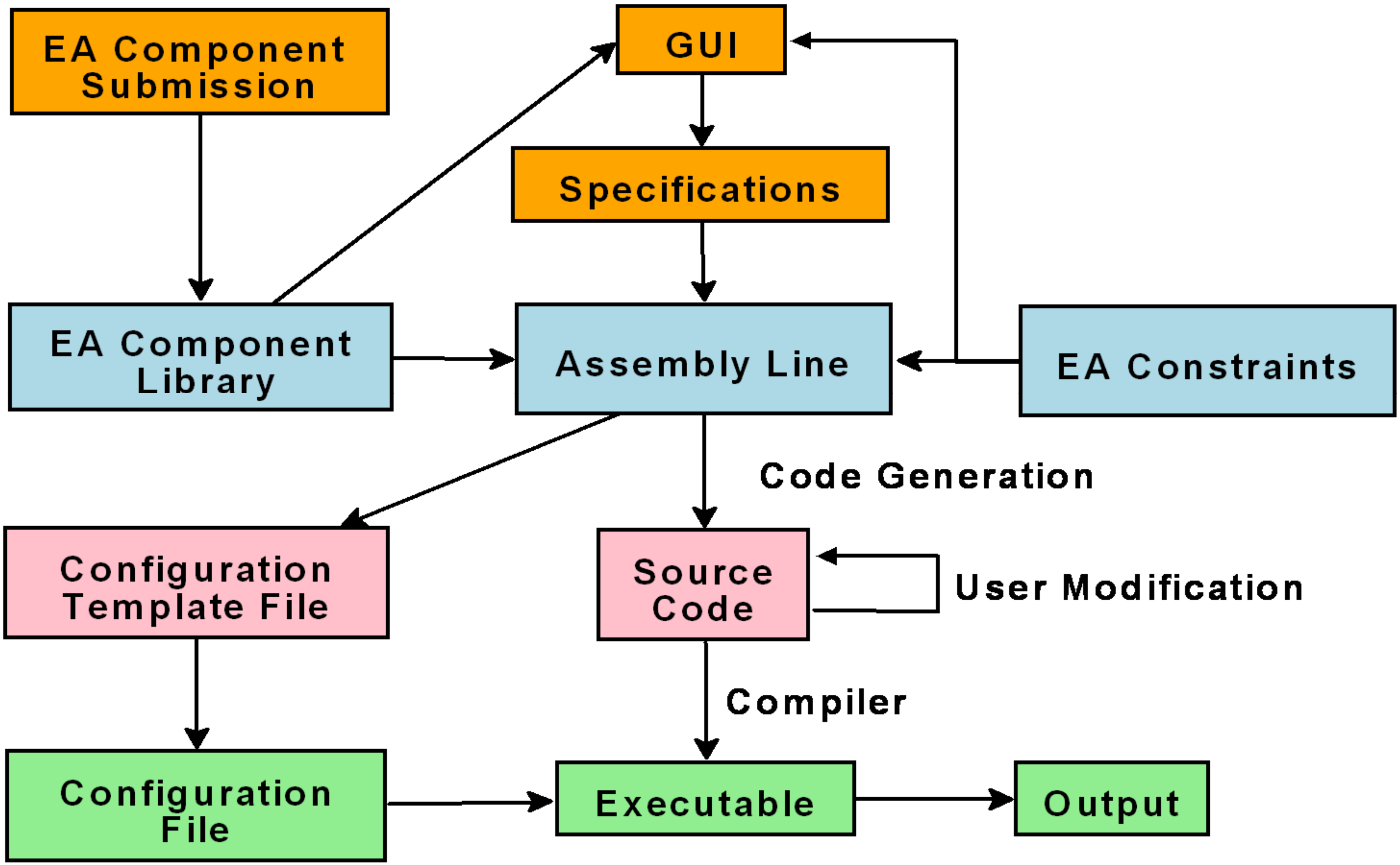
Grand Challenges in EC

- Lack of Reproducibility of Experiments
- Overcoming the No Free Lunch Theorem
- Bridging the Gap between Theory & Practice
- Developing a Science for Parameter Tuning
- Developing a Science for Parameter Control
- Making EAs User Friendly for Non-EA Experts

Lack of Reproducibility of Experiments

- Lack of accepted benchmark problems
- Measuring performance is a tricky business
- Lack of standard algorithms & implementations
- Rich configurations require careful specification
- Pseudo-Random Number Generators matter
- Stochastic algorithms require statistical analysis

Evolutionary Algorithm Software Factory (EA-SOFA)



Grand Challenges in EC

- Lack of Reproducibility of Experiments
- Overcoming the No Free Lunch Theorem
- Bridging the Gap between Theory & Practice
- Developing a Science for Parameter Tuning
- Developing a Science for Parameter Control
- Making EAs User Friendly for Non-EA Experts

No Free Lunch (NFL) Theorem

Informal definition:

All non-revisiting black box search heuristics have equal performance, for any measure of performance, when averaged uniformly over the space of all discrete optimization problems.

Overcoming the NFL Theorem

- Realize that we're not interested in all problems
- Bad news: original 1997 NFL paper [1] sharpened in 2001 to any problem class closed under permutation [2]
- More bad news: in 2003 NFL was shown to apply to multi-objective optimization [3]
- Finally some good news: in 2005 coevolution was shown to exhibit free lunches [4]

NC-LAB loves free lunches!

- Showed coevolutionary free lunches for Maximization over all Test Cases [5]
- Showed free lunches for Pareto Coevolution (a relaxation of traditional multi-objective evolutionary optimization) [6]

For everything you've ever wanted to know about NFL but were afraid to ask, see:
http://www.no-free-lunch.org/

Grand Challenges in EC

- Lack of Reproducibility of Experiments
- Overcoming the No Free Lunch Theorem
- Bridging the Gap between Theory & Practice
- Developing a Science for Parameter Tuning
- Developing a Science for Parameter Control
- Making EAs User Friendly for Non-EA Experts

The Theory & Practice Gap

Theory side of gap:

Rigorous run-time proofs for simplified EAs on artificial benchmark problems

Practice side of gap:

Mountains of experimental data of applying EAs to specific real-world problem instances

Bridging the Theory & Practice Gap

- Scalability through approximation [7]
- The New Experimentalism [8]
- Taxonomy of “natural” problem classes based on non-closure under permutation with corresponding free lunch proofs

Grand Challenges in EC

- Lack of Reproducibility of Experiments
- Overcoming the No Free Lunch Theorem
- Bridging the Gap between Theory & Practice
- Developing a Science for Parameter Tuning
- Developing a Science for Parameter Control
- Making EAs User Friendly for Non-EA Experts

Parameter Tuning: What Needs Tuning

Standard EA Operators:

Parent selection, mate pairing, recombination, mutation, survival selection, termination condition

Standard EA Parameters:

Population size, initialization related parameters, parent selection parameters, number of offspring, recombination parameters, mutation parameters, survivor selection parameters, termination related parameters

Parameter Tuning Overview

Methods:

- Stock values
- Manual
- Monte Carlo sampling on few short runs
- Meta-tuning algorithm (e.g., Meta-EA)

Challenges:

- Exhaustive search infeasible, even assuming independency of parameters (which they're not)
- Optimal values are problem dependent

Developing Parameter Tuning Science

- After decades of research, no efficient parameter tuning methods exist
- The problem space of parameter tuning is not well understood
- Parameter tuning is a class of optimization problem in its own right
- Does NFL hold for parameter tuning class?

References (1)

[1] David Wolpert and William Macready. No Free Lunch Theorems for Optimization. IEEE Transactions on Evolutionary Computation, 1(1):67-82, April 1997.

[2] C. Schumacher, M. D. Vose, and L. D. Whitley. The No Free Lunch and Problem Description Length. In Proceedings of the Genetic and Evolutionary Computation Conference - GECCO 2001, pages 565-570. Morgan Kaufmann, 2001.

[3] David Corne and Joshua Knowles. No Free Lunch and Free Leftovers Theorems for Multiobjective Optimization Problems. In Proceedings of the Evolutionary Multi-Criterion Optimization (EMO 2003) Second International Conference, pages 327-341. Springer LNCS, 2003.

[4] David Wolpert and William Macready. Coevolutionary Free Lunches. IEEE Transactions on Evolutionary Computation, 9(6):721-735, December 2005.

[5] Travis C. Service and Daniel R. Tauritz. A No-Free-Lunch Framework for Coevolution. In Proceedings of the Genetic and Evolutionary Computation Conference - GECCO 2008, pages 371-378, Atlanta, Georgia, July 12-16, 2008.

[6] Travis C. Service and Daniel R. Tauritz. Free Lunches in Pareto Coevolution. Submitted to the Genetic and Evolutionary Computation Conference - GECCO 2009.

References (2)

[7] Hsin-yi Jiang, Carl Chang, Daniel Tauritz, Shuxing Cheng, Taiming Feng, and Travis Service. A Framework for Estimating the Applicability of GAs for Real-World Optimization Problems, In review by IEEE Transactions on Evolutionary Computation.

[8] Thomas Bartz-Beielstein. Experimental Research in Evolutionary Computation: The New Experimentalism. Natural Computing Series. Springer, 2006.

Continued in Grand Challenges in Evolutionary Computing: Part II