

CSE/ECE 848

Introduction to

Evolutionary Computation

Module 3, Lecture 15, Part 3

Machine Learning Enhanced

Evolutionary Computation

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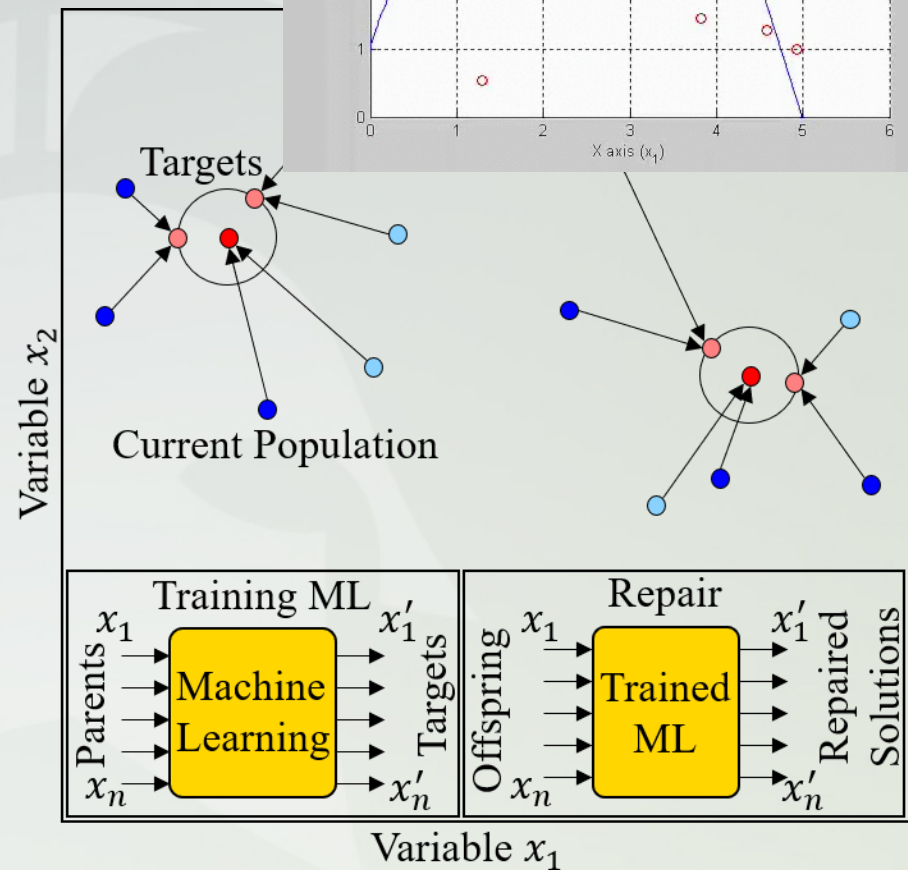
Koenig Endowed Chair Professor

Content

- Machine learning to improve EC
- Initial population generation
 - Create a uniformly distributed population in the feasible search space
- ML-augmented EC operators
 - Recombination: Find patterns in children using ML and share them with children
 - Mutation: Learn regions of less-dense region and create mutated points there or find most beneficial variable to mutate
- Introduce new operators based on ML
- Better surrogates using Auto-Encoders
- History based update operator (“Innovized” repair)

"Innovized" Repair Operator

- Targets: Current best pop members (output)
- Past clustered pop members (Input)
- Train an ANN to learn the relationship
- Apply Trained ML to repair an offspring pop member (input) to create an updated member (output)
- Apply after a few generations



Reference: K. Deb, S. Mittal, D. K. Saxena and E. Goodman (in press). Embedding a Repair Operator in Evolutionary Single and Multi-Objective Algorithms – An Exploitation-Exploration Perspective. *Proc. of Evolutionary Multi-criterion optimization (EMO-2021)*. Springer.

EC with IR Operator

Algorithm 1 Generation t of EA with IR operator

Require: Parent population P_t , Archive A_t .

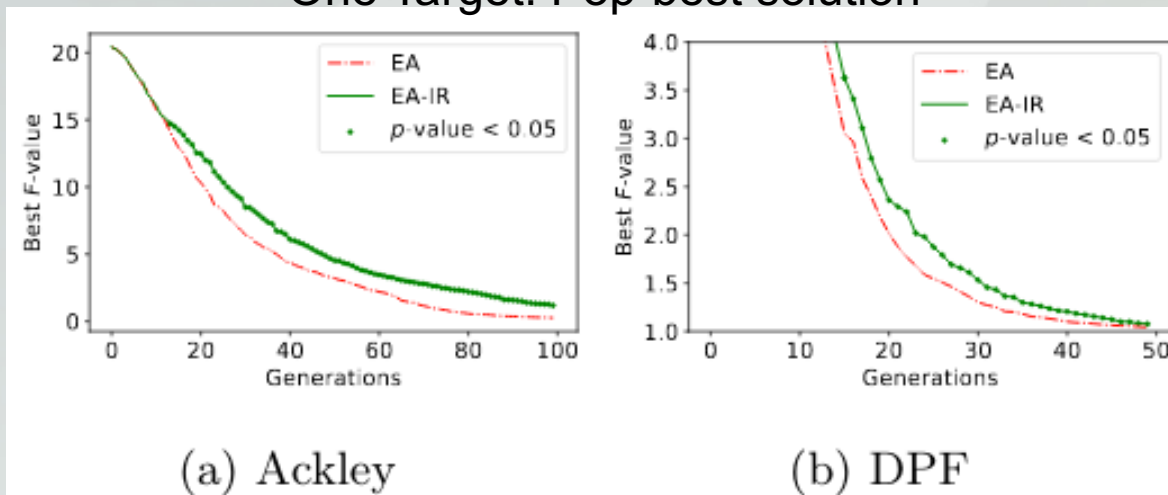
- 1: $A_t \leftarrow A_T \cup P_t \setminus P_{t-t_{past}}$ % Archive Update
 - 2: $P_{mating} \leftarrow$ Tournament Selection on P_t
 - 3: $Q_t \leftarrow$ Crossover and mutation on P_{mating}
 - 4: $T \leftarrow$ Variable vector(s) of target solution(s) identified from P_t Choose Diverse solutions
 - 5: $X \leftarrow$ All variable vectors in A_t
 - 6: $D \leftarrow$ Map the solutions in X to T
 - 7: $D \leftarrow$ Dynamic normalization of D %using equation 1
 - 8: $Model \leftarrow$ Train the ANN using D
 - 9: $Q_t \leftarrow$ Repair randomly selected 50% offsprings Q_t using $Model$
 - 10: Evaluate Q_t
 - 11: $P_{t+1} \leftarrow$ Survival Selection on $P_t \cup Q_t$
 - 12: **return** Next Parent Population P_{t+1}
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$$x_k^{\min} = 0.5(x_k^{l,t} + x_k^l), \quad x_k^{\max} = 0.5(x_k^{u,t} + x_k^u).$$

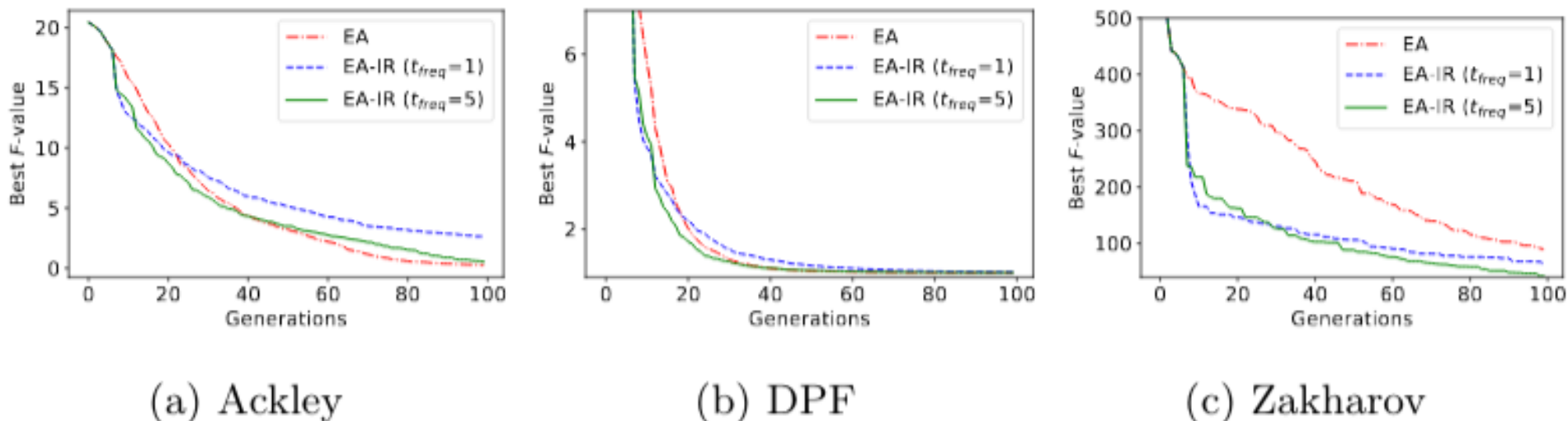
EC with IR Operator Results

One Target: Pop-best solution

IR does not perform well



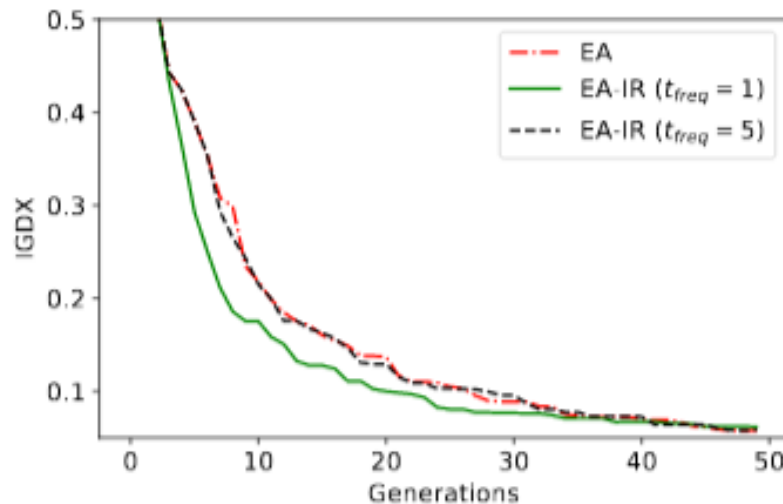
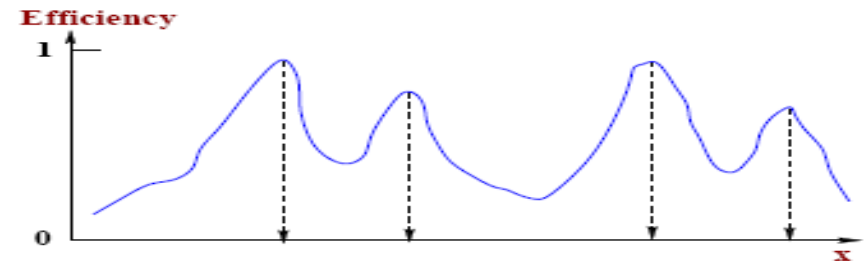
Multiple Targets from Population



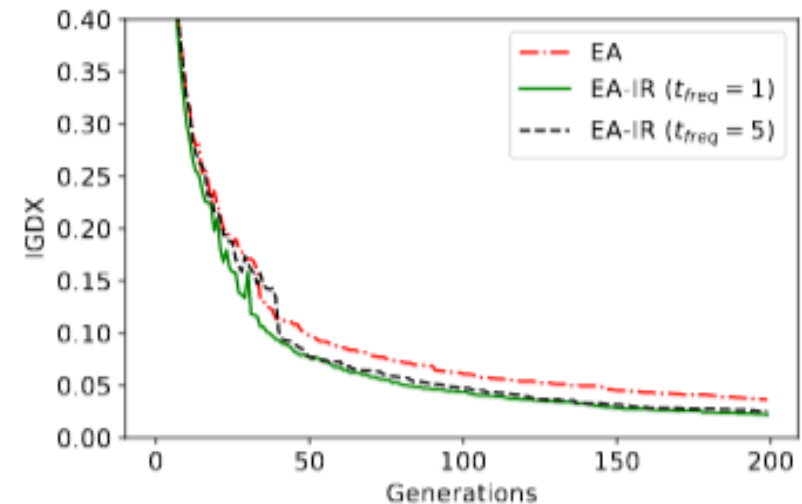
IR performs well

Multi-Modal Optimization

- Cluster-based identification of multiple but diverse targets (Lecture 4, Module 16, Part 3)
- Find multiple optimal solutions in one run



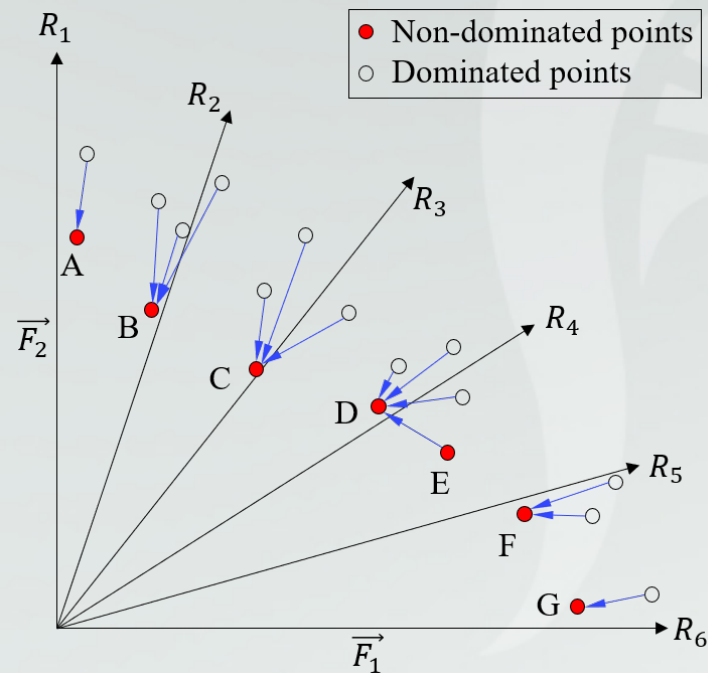
(a) Himmelblau Problem ($n = 2$)



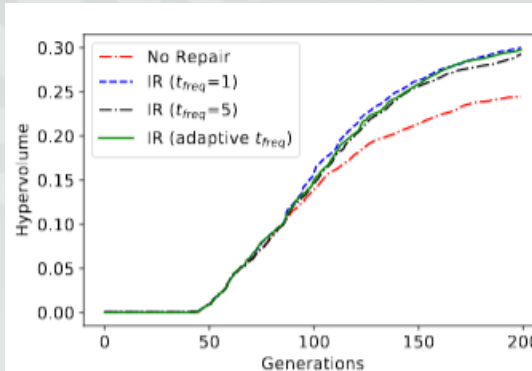
(b) MMP Problem ($n = 15$)

Multi-Objective Optimization

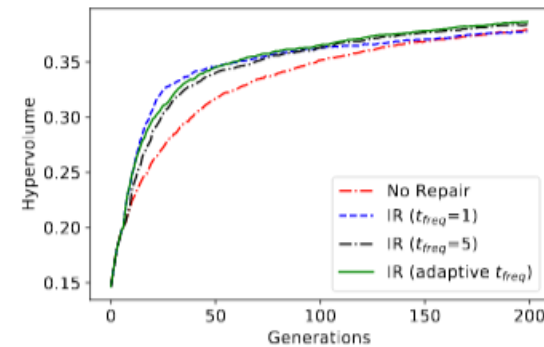
- Idea applicable to multi-objective optimization (Lecture 4, Module 17, Parts 1-3)
- Multiple Targets based on reference lines



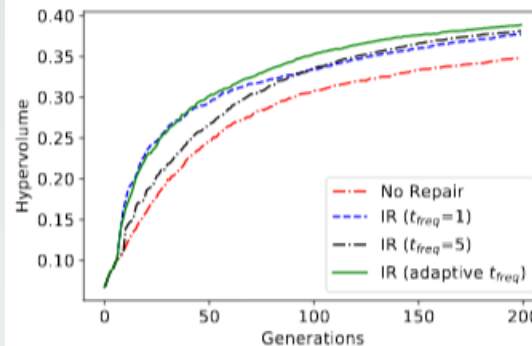
Higher Hypervolume,
Better Performance



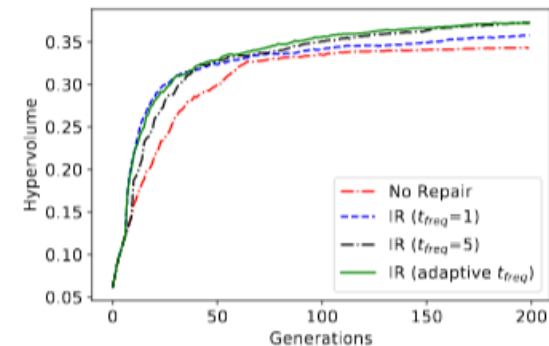
(a) ZDT6



(b) WFG4



(c) WFG6

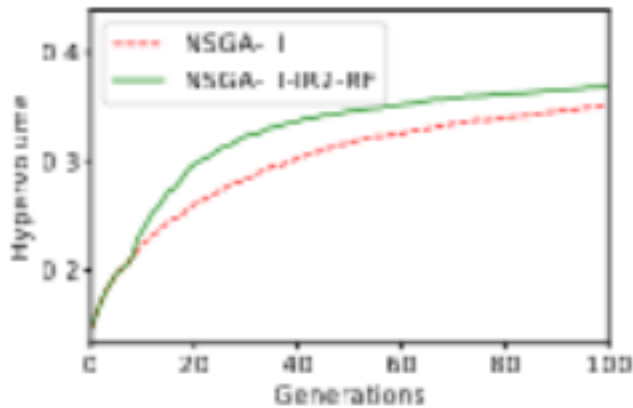


(d) WFG9

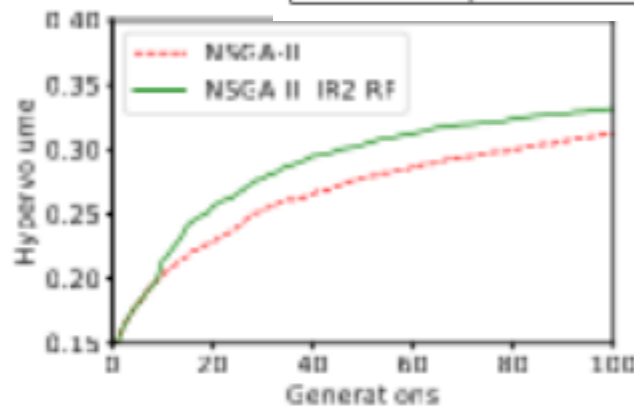
Enhanced IR with Random Forest

- ANN is replaced with RF
- IR2 is slight modification

Problems	NSGA-II-IR-ANN	NSGA-II-IR-RF	<i>p</i> -value
ZDT1	0.679193	0.680198	8.98E-11
ZDT2	0.345448	0.346683	1.33E-11
ZDT3	0.535027	0.535561	1.62E-11
ZDT4	0.680704	0.681041	4.93E-04
ZDT6	0.333949	0.304714	1.40E-05



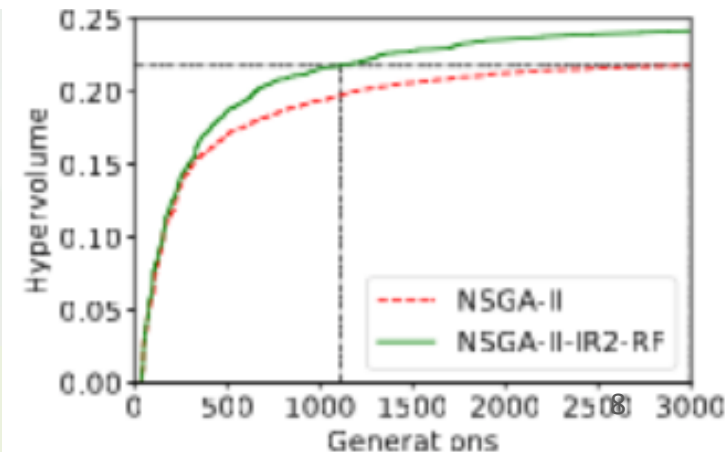
(a) WFG4 ($M = 3$)



(b) Modified WFG4 ($M = 3$)

Gear-box Design with 28 variables, 90 constraints
63.3% Reduction in FEs

- RF performs much better than ANN
- MOEA/D's performance improves with IR2



Mittal, S., Saxena, D., [Deb, K.](#) and Goodman, E. (2020). *Enhanced Innovized Repair Operator for Evolutionary Multi- and Many-objective Optimization*. COIN Report No. 2020020. <https://www.coin-lab.org>

End of Module 3, Lecture 15, Part 3

- Machine learning methods can be used to improve performance of EC and EC's application
- Learn from past populations about progress of solutions
 - Find target solutions from current population
 - Map them with past solutions
 - Train an ML system
- Use the learned ML to update offspring created by genetic operators
- Better performance in uni-modal, multi-modal and multi-objective problems
- IR concept implemented successfully with various EC methods