Adaptive Operator Selection via Online Learning and Fitness Landscape Metrics

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Adaptive Crossover Selection

Different crossover operators might lead to offspring with different characteristics:

- Exploration
- Fitness
- Good traits transmission

We can expect different search results on certain instances.
Adaptive Crossover Selection

Adaptively select the best crossover operator to use during the search process.

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<td>A</td>
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<td>C</td>
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<td>8</td>
<td>D</td>
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Adaptive Crossover Selection: Dynamic Scenario

Dynamic scenario:

- **Different periods** of the search might have different best crossover operators;
- **Dynamic** ACS potentially better than static scenario
Research Questions

1. State-of-the art approaches for Credit Assignment consider the use of just one measure (usually fitness). Enough to characterize the current population distribution?

2. What Operator Selection Rule can handle a set of measures?
Fitness Landscape Analysis (FLA): create a more “aware” snapshot of the current population distribution.

1. perform a set of 4 online FLA techniques during each generation;
   1. Average Escape Probability\(^1\) (Evolvability);
   2. Average \(\Delta - \text{Fitness}\) of the neutral networks \(^2\) (Neutrality);
   3. Average neutrality ratio \(^2\) (Neutrality);
   4. Dispersion Metric\(^3\) (Population Distribution);

2. FLA not to predict hardness but to learn more the current population distribution.

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\(^1\) Lu, G., Li, J., Yao, X. - "Fitness-probability cloud and a measure of problem hardness for evolutionary algorithms" - 2011

\(^2\) Vanneschi L., Pirola Y., Collard P. - "A Quantitative Study of Neutrality in GP Boolean Landscapes" - 2006

\(^3\) Lunacek M., Whitley D. - "The Dispersion Metric and the CMA Evolution Strategy" - 2006
RQ2: Credit Assignment through Online Learning

- Detection of changes **analogous** to Concept Drift tracking in Online Learning;
- **Concept Drift**: change of the underlying distribution of the samples during the learning process;
- Online learning can be used to learn the relationship between FLA results (input features) and the credit measure (output feature);
- **Dynamic Weighted Majority** (DWM) using Regression Trees as base learners.
Dynamic Weighted Majority

DWM(\(p, \beta, \theta, \tau\));
initialize a set of experts and assign an initial weight \(w_j = 1\) to each;
create a window of the last training instances \(wTS(x_i)\);
forall the instances \((x_i, y_i)\) do
    update \(wTS\);
    forall the expert \(e_j\) do
        \(\lambda^i = \text{predict}(e_j, x_i)\);
        if \(|\lambda^i - y_i| < \tau \text{ and } i \mod p = 0\) then
            \(w_j = \beta \times w_j\);
        end
        if \(w_j < \theta \text{ and } i \mod p = 0\) then
            delete expert \(e_j\);
        end
    end
    normalize weights (maximum weight equal to 1);
    calculate global prediction \(\sigma^i\) (weighted average prediction);
    if \(|\sigma^i - y_i| < \tau \text{ and } i \mod p = 0\) then
        create new expert \(e_j\) and train with \(wTS\);
    end
    train all experts with the new instance \((x_i, y_i)\);
end
return \(\sigma^i\);
Case Study: Crossover Operator Selection using the MAENS algorithm for Capacitated Arc Routing Problem \(^4\);

Considers the use of a suite of **four different crossover operators**;

Credit Assignment Mechanism: Proportional Reward (PR);

we exploit the Local Search of MAENS* to perform the FLA techniques without extra computational cost.

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\(^4\)K. Tang, Y. Mei, X. Yao - "Memetic Algorithm with Extended Neighborhood Search for Capacitated Arc Routing Problems" - 2009
Credit Assignment Mechanism: percentage of offspring generated by each operator surviving to the next generation.

\[
PR(i)^t = \frac{|x \in \text{pop}^{t+1} : x \text{ generated by operator } i|}{|\text{pop}^{t+1}|}
\]

- Indirect effect of crossover operator;
- We entrust the selection/ranking operator of the algorithm to evaluate the individuals.
CARP - instance

- Each arc (task) has a service cost and a demand;
- Constraints: number of vehicles and capacity;
- Objective function: minimize the total service cost;
- Proved NP-Hard in 1981;
- Many real-world applications (e.g., waste collection, road gritting).
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MAENS*-II

FLA is performed during each iteration;
- basic Operator Selection Rule: largest *instantaneous* reward in order to reduce bias of previous performances;
- Credit Assignment through DWM.
Experimental studies

- Experiments conducted on a set of 42 non-easy CARP instances belonging to egl, val and Beullen’s benchmark sets;
- Average fitness values calculated over 30 independent runs;
- In order to provide a lower bound and a term of comparison for the results, an Oracle using only the Proportional Reward is built;

1. Tested **optimization** results against MAENS*, Oracle;
2. Tested **prediction** ability against Oracle.
MAENS*-II vs MAENS*

- MAENS* - uses MAB and Proportional Reward;
- MAENS*-II wins the comparisons with MAENS* on 20 instances and loses on 18 out of 42 instances;
- Wilcoxon signed-rank test over the set of the instances suggests that there is no statistical difference between the results achieved by the two algorithms;
- 6 instances show statistically different results using Wilcoxon rank-sum test on each couple of results.

<table>
<thead>
<tr>
<th>Instance</th>
<th>MAENS*-II</th>
<th>MAENS*</th>
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<tbody>
<tr>
<td></td>
<td>avg fitness</td>
<td>std</td>
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<tr>
<td>D23</td>
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<tr>
<td>E15</td>
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<td>732.50</td>
<td>9.64</td>
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<td>12.70</td>
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<td>egl-s2-B</td>
<td>13171.41</td>
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MAENS*-II vs Oracle

- Oracle achieves better results on 40 instances;
- On 2 instances MAENS*-II managed to achieve better results than the Oracle;
- If Oracle shows bound using only PR, then the use of FLA+PR can enhance of the optimization ability of the algorithm.
Prediction Ability: Oracle

Figure: Oracle Selection Rates on instance egl-s2-B
Prediction Ability: MAENS*

![Graph showing MAENS* selection rates on instance egl-s2-B.](image)

P. Consoli (University of Birmingham)

The 43rd CREST Open Workshop
Prediction Ability: MAENS*-II

![Graph of MAENS*-II Selection Rates on instance egl-s2-B]

The graph shows the selection rates for different instances, with lines for gsbx, grx, pbx, and spbx. The x-axis represents the instance numbers, and the y-axis shows the selection rates.
Future work

- Integrated with a Reinforcement Learning mechanism with concurrent use of the operators;
- Tested the use of a diversity-based reward measure;
- Improved results when using RL;
- Outperformed state-of-the-art on Large Scale CARP instances.
Conclusions:

- Novel Adaptive Operator Selection strategy based on a set of FLA measures and online learning;
- Achieved comparable results w.r.t. MAB and outperformed the oracle in a few instances but still non optimal detection of changes in environment;

Future Directions:

- Improving the detection of changes in the environment;
- Test on Software Engineering Problems?
Consoli, P.; Minku, L. L; Yao, X.; "Dynamic Selection of Evolutionary Algorithm Operators Based on Online Learning and Fitness Landscape Metrics", Proceedings of the 10th International Conference on Simulated Evolution And Learning (SEAL’14), LNCS 8886, pp. 359-370, December 2014


This work was supported by UK Engineering and Physical Sciences Research Council (EPSRC) (Grant Nos. EP/I010297/1 and EP/J017515/1).
Thank You!